Essays on Consumers' Willingness-to-Pay for Energy Efficiency: Empirical Evidence for the German Automobile Market

DOCTORAL THESIS

to acquire the academic degree of
doctor rerum politicarum
(Doctor of Economics and Management Science)

submitted to the

School of Business and Economics of
Humboldt-Universität zu Berlin

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Date of Colloquium: November 16, 2018

Abstract

This thesis empirically examines the consumers' willingness-to-pay (WTP) for improvements in fuel efficiency and explores factors related to differences in the consumers' valuation of these improvements. The empirical investigations in the thesis are based on revealed and stated preference data for the German automobile market, with the focus on passenger cars with gasoline and diesel engines. First, the study explores the effects of fuel prices on the market value of fuel economy. Two types of effects are recovered and compared – one corresponds to changes in the budget for driving a car with better fuel economy and the other reflects changes in capital investments in better car quality. Second, the thesis quantifies the valuation of fuel efficiency at the individual level and relates the recovered heterogeneity in consumers' WTP for a reduction in fuel costs to observed consumer- and purchase-related characteristics. The results indicate that a better financial ability, a higher level of education, and brand loyalty facilitate a better understanding of the benefits of investments in fuel-efficient vehicles. Third, consumers' preferences for identical environmental benefits, whether they are presented in terms of improvements in fuel consumption or CO_2 emissions of cars, are compared. Consumers are found to significantly undervalue the benefits of more fuel-efficient vehicles when presented with information on CO_2. The role of individual characteristics in the consumers' WTP for these environmentally important attributes is additionally studied.

Zusammenfassung

Diese Dissertation quantifiziert die Zahlungsbereitschaft (ZB) der Konsumenten für die Verbesserung des Kraftstoffverbrauchs von Personenkraftwagen (PKW) und untersucht die Faktoren, die sich auf die Unterschiede der Verbraucher bei der Bewertung dieser Verbesserungen auswirken. Die empirische Untersuchung in dieser Arbeit basiert auf offenbarten und geäußerten Präferenzdaten für den deutschen Automobilmarkt, wobei der Schwerpunkt auf PKW mit Otto- und Dieselmotoren liegt. Zuerst werden die Auswirkungen von Kraftstoffpreisen auf den Marktwert der Kraftstoffeffizienz untersucht, wobei zwischen Änderungen im Budget für die Nutzung eines Autos mit niedrigerem Kraftstoffverbrauch und Änderungen im Budget für dessen Kauf unterschieden wird. Anschließend ermittelt diese Dissertation die Bewertung der Kraftstoffeffizienz auf individueller Ebene und setzt die Heterogenität der Verbraucher bezüglich der Zahlungsbereitschaft für eine Senkung der Kraftstoffkosten in Beziehung mit beobachteten verbraucher- und transaktionsspezifischen Merkmalen. Die Ergebnisse zeigen, dass eine bessere Zahlungsfähigkeit, ein höherer Bildungsgrad und eine vorhandene Markenloyalität zu einem besseren Verständnis der Vorteile von Investitionen in ein kraftstoffsparendes Fahrzeug führt. Zuletzt werden die Unterschiede in den Präferenzen der Verbraucher für identische Verbesserungen des Kraftstoffverbrauchs und der CO_2-Emissionen quantifiziert. Die Studie zeigt, dass die Verbraucher eine Verbesserung der Kraftstoffeffizienz signifikant höher bewerten als eine entsprechende Minderung der CO_2-Emissionen. Die Rolle der individuellen Merkmale in der ZB von Verbrauchern für diese umweltrelevanten Autoeigenschaften wird zusätzlich untersucht.

Acknowledgments

This thesis has benefited from contributions by several people. First and foremost I would like to express my deep appreciation and gratitude to Prof. Dr. Daniel Klapper, who has been a thoughtful and supportive supervisor throughout, providing advice, encouragement, and support at critical junctures. I am truly fortunate to have had the opportunity to work with him. I also gratefully acknowledge Prof. Dr. Lutz Hildebrandt, Prof. Dr. Till Dannewald, and Prof. Dr. Heiman for their time, positive attitudes, and valuable feedback on my research.

Dr. Daniel Guhl and M.Sc. Narine Yegoryan have been invaluable colleagues in research and teaching. This thesis has benefited greatly from countless discussions with them and from the thorough feedback on my presentations and drafts. I would also like to thank all fellow doctoral students at the School of Business and Economics for their feedback as well as all student assistants at the Institute for Marketing for their assistance in accomplishing many tasks to advance my work on the thesis. Moreover, all studies presented in this thesis have greatly benefited from comments of participants of various workshops and conferences. I am also grateful to Prof. Dr. Franz Hubert, who supported my application for a grant to come to the Humboldt-Universität zu Berlin to pursue a doctoral degree in the first place.

Lastly, I would like to thank my family and friends for their support. A very special gratitude goes out to Dr. Jan Amaru Palomino Töfflinger and Dr. Felix Strobel, who provided moral support throughout the entire process and helped me to take occasional obstacles with equanimity as well as adequately celebrate any progress of the thesis.

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List of Abbreviations

AIC	Akaike information criterion
ADF	Augmented Dickey Fuller
ANOVA	Analysis of variance
ARIMA	AutoRegressive Integrated Moving Average
CI	Confidence interval
cm	centimeter
CO_2	Carbon dioxide
Cov	Covariance
CPI	Consumer price index
DCM	Discrete choice model
EFO	Environmentally friendly option
EnvC	Environmental costs
EU	European Union
FC	Fuel consumption
FE	Fuel economy
FOC	First order condition
FP	Fuel price
g	Gram
GHG	Greenhouse gases
GEC	"General Environmental Consciousness" (scale)
HP	Horsepower
kg	Kilogram
km	Kilometers
l	Liters
LL	Log-likelihood
MAE	Mean absolute error
MNL	Multinominal logit
MPG	Miles per gallon
MSRP	Manufacturer suggested retail price
MXL	Mixed logit
MSE	Mean squared error
OLS	Ordinary least squares
PVFC	Present-discounted value of fuel costs
RAI	Relative attribute importance
SD	Standard deviation
SE	Standard errors
TC	Total costs
UK	United Kingdom
US	United States
Var	Variance
VW	Volkswagen
WTP	Willingness-to-pay

Chapter 1

Introduction

To reduce environmental pollution and address issues related to climate change due to an increasing level of greenhouse gas (GHG) emissions in the atmosphere, a large number of policies have been developed. Because emissions of carbon dioxide (CO_2), the main GHG that contributes to climate change, and energy consumption are directly linked, improving energy efficiency of energy-using goods has become the primary focus of environmental policies.

Accounting for one third of the final energy consumption, road transport is the second-largest source of GHG in the European Union, whereby passenger vehicles account for 12% of total European Union emissions of CO_2.[1] To promote fuel-efficient and low-carbon vehicles, the European Commission has adopted four policy instruments that include fuel taxation (Directive 2003/96/EC), information provision in the form of car labels (Directive 1999/94/EC), manufacturer-specific standards for new vehicles' fuel economy and CO_2 emissions (Regulation (EC) No 443/2009), and vehicle tax (COM(2012) 756 final).[2] These policies intend to shift choices of economic agents by influencing both the demand and supply side. A fuel tax is equivalent to a carbon tax that prices the negative externality (i.e., a Pigouvian tax) and thus directly influences the car usage as well as the car choices. Information provision in the form of car labels ensures that information on the fuel efficiency and CO_2 emissions of passenger cars is made available to consumers to facilitate informed choices. The specific fuel economy and CO_2 emission targets imposed on car manufacturers for new vehicles restrict the supply of low-efficient products. Lastly, the vehicle tax that is proportional to the car's CO_2 emissions changes the relative prices of products with different fuel efficiency values and thus, aims to influence consumers' decisions towards purchasing more efficient technologies.

[1] https://ec.europa.eu/clima/policies/transport/vehicles/cars_en (accessed: March 08, 2018).
[2] The EU legislation regarding passenger cars can be accessed at https://eur-lex.europa.eu.

The effectiveness of these policies depends on consumers' valuation of improvements in the energy efficiency and CO_2 emissions. Energy efficiency, in general, is defined as energy services provided per unit of energy input (Patterson, 1996). For automobiles, this measure is, for example, presented by fuel economy – distance traveled with a car per unit of fuel consumed (e.g., km/l). A related measure is the fuel consumption (FC) of a vehicle that is reciprocal to fuel economy and is measured in terms of fuel per distance (e.g., l/100 km). Consumers' preferences for these car attributes can be quantified in monetary terms with a measure of willingness-to-pay (WTP) – the maximum amount a consumer is willing to pay for a given quantity of an item (Kalish and Nelson, 1991). In line with the "characteristics" approach, consumers' preferences towards a product are derived from preferences for its attributes and their bundles (Lancaster, 1966). Knowing the consumers' WTP for a specific attribute helps to understand consumers' choices and allows to assess how valuable improvements in the attribute value are to the consumers.

Information on the WTP for improvements in fuel efficiency is crucial from both managerial and policy-making perspectives. Valid WTP estimates are essential for development and pricing of profit-maximizing products (Kohli and Mahajan, 1991; Voelckner, 2006; Breidert et al., 2006), as well as for understanding the welfare implications of different energy policies (Newell and Siikamäki, 2014; Allcott and Taubinsky, 2015; Hackbarth and Madlener, 2016; Grigolon et al., 2017). A more efficient product very often implies a trade-off between higher upfront capital costs to acquire it and (potentially) lower future operating costs from its usage. Economic theory suggests that a "rational" consumer should be willing to invest upfront in better energy efficiency as much as it allows the consumer to save on the expected operating costs given expectations of energy prices and the intensity of product usage. If, however, a consumer is willing to pay less (more) than these savings, undervaluation (overvaluation) of energy efficiency occurs. Although extensive financial investments in car purchases should encourage consumers to compare upfront costs and potential savings in future fuel costs, the results of previous empirical studies have been inconclusive regarding the extent to which consumers' car purchase decisions are in line with optimal (cost-minimizing) behavior (see Greene, 2010; Helfand and Wolverton, 2011 for an overview of the studies). The literature provides various explanations attributed to the different valuations of the economic potential of energy efficiency investment at the market and individual levels (e.g., Allcott, 2011; Gillingham and Palmer, 2014; Gerarden et al., 2015; Metcalf and Hassett, 1999; Tietenberg, 2009 to name a few).

The present thesis contributes to this stream of literature by quantifying the consumers' WTP for improvements in fuel efficiency of passenger cars with gasoline and diesel engines at the German automobile market and by exploring factors related to consumers' differences in the valuation of these improvements. The thesis consists of three self-contained essays presented in the next three chapters. The contributions of the thesis lie in both the conceptual and the methodological domain. On the methodological side, the thesis exploits various data types and statistical techniques to elicit the WTP values for car fuel efficiency. Conceptually, the thesis considers the effects of various determinants, some of which have not yet or only partially been studied in the literature on the consumers' valuation of fuel efficiency. The **first essay** investigates the effects of fuel prices on the market value of fuel economy while distinguishing between changes in the budget for driving a car with better fuel economy and changes in capital investments in better car quality. Revealed preference data, in the form of aggregate market data on vehicle prices and attributes for diesel and gasoline cars, are used to analyze how the differences in attributes of cars are reflected in their prices and to explore co-movements of the vehicle price sensitivity to fuel economy with changes in fuel prices. The investigation in the **second essay** is also based on revealed preference data, but from the observed car purchase transactions at the individual level. This type of data allows to recover the individual valuation of fuel efficiency and to relate the recovered heterogeneity in consumers' WTP for a reduction in fuel costs to observed consumer- and purchase-related characteristics. The **third essay** quantifies the differences in consumers' preferences for identical improvements in FC and CO_2 emissions. Because these two metrics are perfectly correlated, stated preference data from two choice-based conjoint experiments with information either on FC or CO_2 emissions are collected to recover the WTP for FC and CO_2 independently. Using various methodologies and data types for empirical investigations in the thesis, provides an opportunity to gain a more complete understanding of the topic at hand, to use novel sources of identifying variation, and to address several estimation issues discussed in the literature. An overview of advantages and challenges of different preference data and methodologies for eliciting and estimating consumers' WTP is provided, for example, by Voelckner (2006), Miller et al. (2011), and Bateman et al. (2002). The focus and contributions of the essays are next discussed in details.

The **first essay** (chapter two) explores the effects of fuel prices on the market value of fuel economy. To recover this value, a hedonic price model is estimated using aggregate market data on vehicle prices and attributes for diesel and gasoline cars of three sequential model years on the German automobile market. The hedonic price model is based on the assumption that the observed price of a good reflects a combination of implicit values for each of its attributes (Rosen, 1974). Econometrically, the implicit values for product attributes are estimated by regressing the product price on its characteristics. The previous literature has applied the hedonic price regression to study the responsiveness of vehicle prices to fuel prices or fuel economy (Boyd and Mellman, 1980; Goodman, 1983; Atkinson and Halvorsen, 1984; Mulalic and Rouwendal, 2015). The present study advances the prior work by looking at the effects of both these variables and their interaction. In contrast to previous studies, the estimated specification of the hedonic price regression differentiates between the valuation of fuel economy by consumers and their reactions to fluctuations in fuel prices. Thus, two sources of changes in the consumers' WTP for better fuel economy are recovered – changes in the budget for driving a car and changes in the capital investment in better fuel economy. Prior studies could recover only the former source because the marginal benefit of driving a car of a particular fuel economy remained constant, and thus, the increased fuel prices result in a proportional decrease in car usage (e.g., Ohta and Griliches, 1986). The present study shows that, when the marginal benefit of driving a car varies with fuel prices, the total effect of the mentioned two sources of changes in the consumers' WTP for better fuel economy may lead to either a decrease or an increase in the vehicle distance traveled. If the utility from driving a car with better fuel economy exceeds the income effect of higher fuel prices on the driving budget, then the car usage increases. Using the quantified impact of fuel prices on the market value of fuel economy, the implied changes in the kilometers driven with cars and the resulting CO_2 emissions – two crucial outcomes for policy evaluation, are assessed. The analysis recovers values for the considered market outcomes that are in line with the official statistics.

The **second essay** (chapter three) aims at investigating the role of consumer heterogeneity in the valuation of fuel efficiency. It first recovers the individual valuation of expected future fuel costs at the time of a car purchase and then, explores how various consumer- and transaction-specific characteristics relate to the recovered consumers' WTP for a reduction in fuel costs. The empirical investigation in this essay is based on revealed preferences by exploiting household-level survey data on new automobile purchases in Germany over a period of seven years. The richness and structure of the data provide several conceptual and methodological advantages. Conceptually, the analysis in this essay contributes to previous studies by explicitly accounting for the substantial heterogeneity across consumers in their car utilization along with heterogeneity in their tastes for car attributes. The previous literature has stressed the importance of considering the consumer heterogeneity in tastes for products and their attributes (e.g., Kamakura et al., 1996; Allenby and Rossi, 1998; Keane and Wasi, 2013). If consumers are heterogeneous in their tastes and car usage, they may select into different vehicles. A consumer, who expects to drive extensively, may choose either a more fuel efficient vehicle to save money on fuel costs or a larger, more comfortable vehicle to make the long drives more pleasant (West, 2004). As a result, this self-sorting into vehicles based on individual preferences would confound the estimated WTP values because the price of subsequent car utilization is different. Bento et al. (2012), for example, used a simulation to show that ignoring heterogeneity in consumers' tastes and product usage in empirical analyses can significantly affect the estimated WTP values and result in incorrect implications. Methodologically, the individual tastes for a reduction in fuel costs are estimated by using the hedonic discrete choice model – a method that addresses weaknesses of the discrete choice and hedonic price models while estimating the WTP for car attributes. In contrast to the discrete choice model, the distributions of consumer tastes for product attributes are recovered directly from the data without a need to impose any distributional assumptions. Furthermore, there is no need to make assumptions on the total market size and consumer choice sets. The hedonic price model is extended by allowing for heterogeneity in the values for consumers' WTP for product attributes. Additionally, a highly detailed definition of a car type allows to reduce the possible effect of omitted car attributes on the estimation. A joint distribution of consumer tastes and heterogeneity determinants is recovered by applying a quantile regression, which allows to investigate a disparity in the covariates' effects among different levels of the estimated fuel cost valuation. The estimation results indicate that there is a high degree of undervaluation of potential fuel savings – for a €1 reduction in future fuel costs, the consumers are willing to pay no more than €0.20 on average. Consumers' financial ability, education, and stickiness to a previously bought car make as a strategy to reduce choice complexity are found to be the most important determinants of the consumer heterogeneity in valuation of fuel costs.

The **third essay** (chapter four) investigates whether and how consumers differ in their preferences and WTP for identical improvements in FC versus CO_2 emissions of cars. From a technical perspective, these two metrics are linearly connected by a constant factor and thus are equivalent in describing the environmental impact of vehicles. However, it remains unclear whether consumers value improvements in CO_2 as much as improvements in FC. If consumers' car choices vary across metrics, such a shift in choices may lead to negative financial consequences for consumers and higher environmental costs from car use. Although consumers' preferences for a reduction in FC and CO_2 emissions of cars are extremely important in the context of environmental policies, no prior work has directly compared consumers' preferences for them. Prior research on revealed preferences has not been able to separately identify these effects because the metrics are perfectly correlated, and research on stated preferences has either focused on one of these environmentally important attributes or also considered both measures simultaneously and thus did not disentangle the separate effects of each metric. The present study recovers the distributions of the WTP for FC and CO_2 independently based on consumer choices from optimally designed choice experiments and by applying a mixed (random coefficient) logit model. The estimation accounts for consumers' unobserved heterogeneity in tastes for car attributes in addition to the observed heterogeneity in the respondents' socio-demographic characteristics, car use experience, and environmental attitudes and knowledge. Additionally, the differences in the WTP values are explored for diesel and gasoline vehicles. For a rational agent, the presentation of both FC and CO_2 to assess personal fuel costs and the environmental impact of a car option is redundant because each metric presents a "translation" of the same underlying information (Ungemach et al., 2017). However, this study demonstrates that consumers value improvements in FC significantly more highly than the corresponding reduction in CO_2 emissions. Moreover, this discrepancy between the metrics varies with the unit in which the amount of CO_2 emissions is presented. For example, consumers are found to be willing to pay, on average, for only 55% of the fuel savings and environmental benefits from better FC and CO_2 emissions when presented with CO_2 information in kg/km (instead of g/km). The paper's findings suggest that individuals fail to recognize how transport-related CO_2 emissions translate into 'private' costs and ultimately incur higher financial costs than under their optimal choices and cause greater environmental costs for society. These biases persist even when the environmentally friendly product is cost-minimizing.

Table 1.1 provides an overview of the three essays summarizing their key findings, the data studied, and the applied statistical methods. In summary, the present thesis represents a substantive empirical analysis that describes and explains consumer behavior concerning a topic of interest to readers in the areas of microeconomics, economic policy, and marketing. The insights from these essays are useful for policymakers and car manufacturers to understand how persons value improvements in fuel efficiency – an environmentally important car attribute, how to design targeted policies to motivate consumers' choices toward cars with better fuel economy, and how to communicate the environmental benefits of car offers to achieve the pre-specified goals.

Table 1.1: Overview of the essays

	Essay 1 (Chapter 2)	**Essay 2 (Chapter 3)**	**Essay 3 (Chapter 4)**
Title	The Moderating Effect of Fuel Prices on the Market Value of Fuel Economy, Driving Intensity, and CO_2 Emissions	On Factors of Consumer Heterogeneity in the (Mis)valuation of Future Energy Costs: Evidence from the German Automobile Market	Metric and Scale Effects in Willingness to Pay for Environmental Benefits
Contributions	• explicit quantification of the effects of FP on WTP for FE for diesel and gasoline vehicles	• recovering the consumers' WTP for a reduction in fuel costs at the individual level	• quantification of the differences in consumers' preferences for identical improvements in FC and CO_2 (metric effect)
	• identification of two sources of changes in the WTP for FE: (1) changes in the budget for driving a car; (2) changes in capital investments in better FE	• accounting for consumer heterogeneity in car utilization	• exploration of the effects of three scales for CO_2 emissions (0.100 kg/km vs. 100 g/km vs. 10,000 g/100 km) on consumers' preferences and choices (scale effect)
	• allowing marginal benefits of driving a car with a particular FE to vary with FP (prev.: fixed)	• exploration of the determinants of consumer heterogeneity in the WTP	• test for differences in the metric and scale effects by vehicle engine type (diesel vs. gasoline)
Key findings	• significant differences in the market values of FE between diesel and gasoline vehicles and their responsiveness to changes in FP	• consumers undervalue the potential fuel savings from better FE to a high degree	• consumers value improvements in FC significantly more highly than the corresponding reduction in CO_2 emissions
	• utility from driving with better FE exceeds the income effect of higher FP on driving intensity	• significant differences in the individual valuation of reduced fuel costs for diesel and gasoline vehicles of various car classes	• WTP for a reduction in CO_2 is increasing with an expansion of the scale of the numeric information
		• consumers' financial ability, education, and brand loyalty facilitate a better understanding of the benefits of investments in fuel-efficient vehicles	• effects of the framing of information on consumers' preferences are similar for both engine types
Data	observational data (market level)	observational data (consumer level)	choice experiments (within- and between-subject variations)
Type of preferences	revealed	revealed	stated
Statistical methods	multivariate regression (hedonic price model); T-test; ANOVA	nonparametric kernel regression; quantile regression; clustering of variables; T-test; ANOVA	discrete choice models (MNL, MXL); bootstrap method; confirmatory factor analysis; logistic regression; generalized least squares regression; T-test; ANOVA; χ^2-based contingency analysis

Chapter 2

The Moderating Effect of Fuel Prices on the Market Value of Fuel Economy, Driving Intensity, and CO_2 Emissions[1]

Vlada Pleshcheva, Daniel Klapper

Abstract

In the current paper, we quantify the effect that fuel prices have on vehicle prices' responsiveness to fuel economy. We apply a hedonic price model to the German automobile market by using data on detailed technical specifications of high-sales vehicles of three sequential model years. In contribution to previous research, our specification enables us to distinguish between consumers' valuation of fuel economy versus their reaction to changes in fuel prices. Two sources of changes in consumers' willingness-to-pay for better fuel economy are discussed – changes in the budget for driving a car and changes in capital investments in better car quality. We also discuss the subsequent changes in the optimal driving intensity and the resulting carbon dioxide emissions. Differences in the effects are studied for various car makes of both diesel and gasoline engines.

Keywords: CO_2 emissions; fuel economy; fuel prices; hedonic regression
JEL Classification: D12, L62, Q41, Q51.

[1]Presented at the internal seminars; the "Jahrestreffen der Forschungsgruppe 'Konsum und Verhalten"', Göttingen, 18.-20.09.2014; and the AxCon 2016 "Product Marketing Best Practice Day", Berlin, 21.04.2016.

2.1 Introduction

Many previous studies have investigated the role of fuel prices in shaping various market outcomes. Applied to the automobile market, there is a vast body of literature on fuel price effects on automobile market shares (e.g., Klier and Linn, 2010), fleet structure (e.g., Li et al., 2009), the pricing of new and used cars (e.g., Allcott and Wozny, 2014; Busse et al., 2013), and driving intensity (e.g., Frondel and Vance, 2009; Gillingham, 2014). We contribute to the literature by quantifying how exactly fuel prices influence the market value of fuel economy. We use aggregate market data on vehicle prices and attributes for diesel and gasoline cars of three sequential model years (2011 to 2013) on the German automobile market and estimate a hedonic model of automobile prices to explore co-movements of vehicle price sensitivity to fuel economy with changes in fuel prices.

Derived from the utility maximization problem for consumers, the marginal willingness-to-pay for fuel economy contains two terms – the responsiveness of car prices to fuel economy, reflecting capital investments in car quality, and responsiveness to changes in the driving budget. If the price responsiveness to fuel economy does not depend on fuel prices, the only change from an increase in the price of fuel is the increasing per distance unit cost of driving that results in a decrease in vehicle distance traveled. In contrast to previous research, where the marginal benefit of driving a car of a particular fuel economy remained fixed, we allow this benefit to vary with fuel prices. In this case, because the price responsiveness to fuel economy is also a function of fuel prices, there are two sources of changes in the willingness-to-pay for fuel economy. The first source, as in previous research, corresponds to changes in the budget for driving a car, whereas the second source reflects changes in capital investments in better fuel economy. The total effect of these two sources may lead to either a decrease or an increase in the vehicle distance traveled.

Changes in the price responsiveness to fuel economy due to changes in fuel prices may come from both supply and demand side. For example, Ohta and Griliches (1986) argue that if fuel price shocks affect consumer choices, then one should observe corresponding adjustments in automobile prices. Previous research has found that higher fuel prices increase the demand for high-fuel-economy vehicles, pushing up their prices relative to cars with low fuel economy (e.g., Klier and Linn, 2010, Li et al., 2009). At the same time, an increase in fuel prices results in increasing production costs of a better fuel economy for car manufacturers. Both these effects – from the supply and demand side – increase the implicit value of a better fuel economy.

To recover a combined effect of these two sources of change, we use a hedonic price regression, which reflects changes in the equilibrium market prices of a product and, thus, captures an interaction between the supply and demand in each state of the market (Rosen, 1974). Hedonic price regressions have often been applied to the automobile market, which is characterized by high product involvement, a high degree of product differentiation, and rapid rates of product innovation (e.g., Boyd and Mellman, 1980; Triplett, 1969; Requena-Silvente and Walker, 2006). As in the previous work involving hedonic price regressions, we recognize an econometric problem of high collinearity between fuel economy and other car characteristics due to their technological interdependence (see Knittel, 2012 for a study on the technological interdependence of car attributes). To overcome this problem, we control for advances in fuel efficiency rather than advances in fuel economy itself. We define fuel efficiency as fuel economy multiplied by the horsepower of a car. This measure thus reflects a service output measured in kilometers driven with a car of a specific performance per unit of energy input (Patterson, 1996; Sprei et al., 2008). Because horsepower is negatively correlated with fuel economy, the computed fuel efficiency provides a more suitable measure of advances in car quality. In contrast to studies that use a combined measure presented by fuel operating costs, i.e., the costs of fuel per distance driven (Klier and Linn, 2010), the current paper explicitly investigates the role of fuel prices as a moderator of the market value of fuel economy. Thus, we can differentiate between consumers' valuation of fuel economy versus their reaction to changes in fuel prices.

Our paper is closely related to Busse et al. (2013) and Busse et al. (2016). These two papers show how changes in fuel prices affect equilibrium car prices and the sales of both new and used vehicles of different fuel economies. Busse et al. (2016) focus on the car manufacturers and their associated dealerships, whereas Busse et al. (2013) focus on the consumer side. Jacobsen and Van Benthem (2015), while investigating the effect of gasoline prices on vehicle scrappage decisions, also measure the relation between gasoline prices and the valuation of used vehicles. These three studies find that cars with high fuel economy are less sensitive to an increase in fuel prices, i.e., the slope of the car price gradient with respect to fuel prices becomes less negative. Thus, there is a positive relationship between the fuel economy of a car and changes in car prices with respect to fuel prices. We reverse the logic of these studies and explore the responsiveness of vehicle prices to fuel economy, depending on the fuel price. Accordingly, we expect to have a positive relationship between the price gradient of fuel economy and fuel prices. Our study differs from the ones mentioned above in that they do not aim and are not able to recover the market value of fuel economy because the authors include fuel economy as a categorical variable in their specification. We include both fuel economy and fuel price as continuous variables, and by including a term for their interaction into a price regression, we can look at the effects that fuel prices have on the market value of fuel economy. The specification we use provides an advantage over previous work in that it allows us to use the quantified impact of fuel prices on market valuation of fuel economy in a subsequent analysis to access the implied changes in the kilometers driven with cars and resulting CO_2 emissions – two important outcomes for policy evaluation. Additionally, because we look at the variation in car prices at the time of market entry, we do not need to account for possible rebates and differences in the bargaining power between sellers and buyers.

Applied to the German automobile market, the consumers' willingness-to-pay[2] for reduced fuel consumption is examined by only a few authors. Achtnicht (2012), for example, studies the importance of CO_2 emissions per kilometer and fuel costs in € per 100 km for car choices in Germany based on the mixed logit model with data from a choice experiment. In contrast, the current paper uses data on the observed vehicle attributes and their prices. Fetscherin and Toncar (2009) use the hedonic price regression to uncover the valuation of the brand equity and other attributes in the German automobile market. However, the authors exploit the ratings for several categories of attributes instead of car characteristics themselves, which might not fully reflect their relation to vehicle prices.

In our analysis, we focus on vehicles from compact and middle classes. These two car classes are characterized by stable high market shares and high supply relative to other car types. For example, based on the data used in this study, 25.6% and 12.6% of new passenger car registrations in 2013 belonged to compact and middle classes, respectively, and accordingly amounted to 27% and 17% in the total passenger car fleet. Vehicles from larger car classes (e.g., Mercedes S from the upper class) might be used predominantly for business trips, resulting in a smaller importance of adjustments in fuel economy to high fuel prices. We argue that the selected car classes represent the market and average technological patterns best. We also focus on cars that have been issued on the market over 2011-2013, a period after major policy reforms related to the German automobile branch were introduced (e.g., the scrappage policy in 2009; the adjustment of the vehicle annual circulation tax in 2009; and information disclosure in the form of fuel economy and CO_2 emissions labeling that came into force in 2011), after the car market and fuel prices recovered from the financial crisis of 2008-2009, and before the scandal relating to the emissions from diesel engines began in 2014.

[2]Within the context of the current paper, we use the terms "willingness-to-pay" and "market value" interchangeably, as the latter also reflects the former.

The majority of previous studies have focused primarily on gasoline vehicles because these studies are based on data from the US market, where diesel-fueled vehicles constitute only 3% of the total fleet (as of 2014[3]). This paper, in contrast, compares the effects for both diesel and gasoline cars and belongs to studies on the European automobile market (e.g., Dahl, 2012; Delsaut, 2014; Frondel and Vance, 2009). In Germany over 2011-2013, the share of diesel vehicles, on average, accounted for 48% of the total new passenger car registrations and 30% of the total passenger car fleet; the rest of both new passenger car registrations and passenger car fleet belonged to gasoline vehicles, with only tiny shares (less than 2%) of alternative engine types (e.g., hybrid, electric, etc.).[4]

Our results indicate that there are significant differences in the market values of fuel economy between diesel and gasoline vehicles and their responsiveness to changes in fuel prices. Diesel cars are characterized by a larger elasticity of the price gradient of fuel economy to fuel prices compared to gasoline cars. This finding can be explained by a relatively higher popularity of diesel cars on the German market. Car manufacturers have developed technologies to improve the fuel economy of diesel cars in response to a growing demand from the consumer side. Because the diesel fuel price is lower than that for gasoline due to a favorable fuel tax on diesel, while capital investments in diesel cars are higher, buyers who decide to purchase diesel cars might also be characterized by a higher sensitivity to fuel prices at the time of a car purchase. Both factors lead to a higher elasticity of the price gradient of fuel economy to fuel prices for diesel vehicles.

Relying on the rationality assumption in the consumer choice problem, we also recover the implied optimal driving intensity based on the estimated market values of fuel economy for both engine types and the corresponding total CO_2 emissions. The resulting values of car usage and CO_2 emissions are close to the official statistics for the German automobile market. This finding highlights the reliability of the results. In contrast to the majority of previous studies measuring the elasticity of driving intensity to fuel prices as being constant, the methodology of this paper allows for a nonlinear dependency between driving intensity and fuel prices that better reflects adjustments of consumers' driving patterns to changes in fuel prices.

The remainder of the paper is organized as follows. In section 2.2, we present the methodology and describe data used for the analysis. Section 2.3 presents the results of the empirical analysis. The section 2.4 discusses the implications of the findings and concludes.

[3]http://de.statista.com/statistik/daten/studie/473962 (accessed: October 08, 2017).
[4]https://de.statista.com/statistik/daten/studie/251779 and https://de.statista.com/statistik/daten/studie/184465 (accessed: October 08, 2017).

2.2 Estimation Approach

This paper uses a hedonic price regression to recover consumers' willingness-to-pay for marginal improvements in fuel economy, while controlling for all other car attributes, and to examine how fuel price fluctuations affect this value, consumers' implied optimal driving intensity, and CO_2 emissions. In the following, we present the model, describe the data, and specify the hedonic price regression we use for the analysis.

2.2.1 Model

The hedonic price model is based on the assumption that the observed price of a durable good reflects a combination of implicit values for each of its attributes (Rosen, 1974). Implicit prices for product attributes result from an intersection between an offer curve from the supply side and a bid function from the demand side. The hedonic price function is assumed to be exogenous for both parts of the bargain.

In application to the automotive market, a representative consumer derives utility from driving a car with quality X and fuel economy (in km/liter) and consuming all other goods that are treated as a single composite C. The consumer chooses a car that provides the highest utility given her own budget, which is distributed among a purchase of a vehicle ("initial investments"), the utilization of the car ("budget for driving"), and consumption of the composite good. The budget for a vehicle purchase is represented by the hedonic price function, whereas the budget for driving can be formalized as a product of price per kilometer (p_{km}) and the expected driving intensity (Km) over the period of car ownership. For a given car, p_{km} depends on its fuel economy (FE) and fuel price (FP) in €/liter, i.e. $p_{km} = \mathrm{FP}/\mathrm{FE}$ (€/km).

Formally, the consumer's problem can be represented by the system of equations 2.1, where X is a vector of car attributes other than fuel economy, $\mathbf{p}(\cdot)$ is the hedonic price function, Y is the consumer's income, and the price of the composite good (C) is normalized to unity. The hedonic price function is a functional dependence of the price of a car on its attributes.

$$\begin{cases} \max \ \mathrm{U(X,\ FE,\ Km,\ C)} \\ \text{s.t.} \ \ \mathrm{Y} \geq \mathbf{p}(\mathrm{X}, \mathrm{FE}) + p_{km} \times \mathrm{Km} + \mathrm{C} \end{cases} \tag{2.1}$$

In equilibrium, the budget constraint is binding, and for continuous product attributes, the first-order condition (FOC) for a chosen product must hold. From the FOC, the marginal rate of substitution between a product attribute X_q and the composite commodity C equals the partial derivative of the hedonic price function with regard to the attribute. Thus, Equation 2.2 defines the implicit price or marginal willingness-to-pay (MWTP) for each car attribute.

$$\mathrm{MWTP}(\mathrm{X}_q) = \frac{\partial u(\cdot)}{\partial X_q} / \frac{\partial u(\cdot)}{\partial C} = \frac{\partial \mathbf{p}(X, FE)}{\partial X_q} \tag{2.2}$$

In contrast to Ohta and Griliches (1986) and Atkinson and Halvorsen (1984), we include the fuel economy of a car into the utility function and argue that it is important since there may be a direct effect of fuel economy on the utility of driving a car (aside from its effect on the budget constraint) through its direct connection to the environmental impact (i.e., consumers with higher environmental concern may derive higher utility from better fuel economy after accounting for savings in the fuel costs via the budget constraint). Because the price per kilometer also depends on fuel economy, the willingness-to-pay for fuel economy that results from the FOC includes an additional term along with the hedonic price gradient (Equation 2.3).

$$\mathrm{MWTP}(\mathrm{FE}) = \frac{\partial u(\cdot)}{\partial FE} / \frac{\partial u(\cdot)}{\partial C} = \frac{\partial \mathbf{p}(X, FE)}{\partial FE} - FP \times \frac{Km}{FE^2} \tag{2.3}$$

The willingness-to-pay for marginal improvements in fuel economy is expected to be positive (i.e., $\mathrm{MWTP(FE)} > 0$) and to correspond to the law of diminishing marginal utility for an "economic good" (i.e., $\partial\mathrm{MWTP(FE)}/\partial\mathrm{FE} < 0$). In the case of an increasing fuel price, MWTP(FE) will decrease as a result of the increased costs of driving a car ("income effect").

$$\frac{\partial \mathrm{MWTP(FE)}}{\partial \mathrm{FP}} = -\frac{Km}{FE^2} < 0 \tag{2.4}$$

However, in our application, we would like to allow the price gradient to vary with fuel prices. It will thus reflect changes in the market valuation of a car's fuel economy due to changes in the fuel price. To do this, we must add a fuel price variable into the price regression along with its interaction with fuel economy. We expect the following relationships to hold:

$$\begin{cases} \dfrac{\partial \mathbf{p}(\cdot)}{\partial \mathrm{FP}} < 0 \text{ for } \mathrm{FE} < \mathrm{FE}^* \\ \dfrac{\partial \mathbf{p}(\cdot)}{\partial \mathrm{FP}} > 0 \text{ for } \mathrm{FE} > \mathrm{FE}^* \\ \dfrac{\partial}{\partial \mathrm{FE}} \left(\dfrac{\partial \mathbf{p}(\cdot)}{\partial \mathrm{FP}} \right) > 0 \end{cases} \tag{2.5}$$

The first two conditions in (2.5) suggest a decrease in the price of a vehicle if the value of fuel economy falls below a certain threshold (FE^*) and an increase in the price otherwise (similar to Jacobsen and Van Benthem, 2015 and Busse et al., 2013). The sign of the price derivative with respect to the fuel price also depends on the prevalence of the effect from either increased production costs (positive) or decreased consumer income (negative). The third condition implies that vehicle prices are less sensitive to changes in fuel prices with increasing fuel economy. Due to the symmetry of the second derivative, this condition also implies that $\partial/\partial\mathrm{FP}\left(\partial \mathbf{p}(\cdot)/\partial \mathrm{FE}\right) > 0$. The net effect of fuel prices on MWTP(FE) then depends on the magnitudes of both terms on the right-hand side of Equation 2.6. The first term corresponds to the changes in the capital investments in a better fuel economy with changing fuel prices, while the second term reflects the changes in the budget for driving a car.

$$\frac{\partial \mathrm{MWTP(FE)}}{\partial \mathrm{FP}} = \frac{\partial}{\partial \mathrm{FP}} \left(\frac{\partial \mathbf{p}(\cdot)}{\partial \mathrm{FE}} \right) - \frac{Km}{FE^2} \lesseqgtr 0 \tag{2.6}$$

Given the utility maximization principle, a consumer chooses a bundle of vehicle attributes in a way that reflects her expected usage of a car at expected realizations of fuel price. Thus, the optimal annual kilometers could be computed based on the assumption that for a marginal improvement in fuel economy, a rational consumer is willing to pay the exact same amount because this additional improvement in fuel economy would allow her to save in fuel costs over a car possession time, T. We take an undiscounted version of the formula for fuel savings from one km/l and equate it to the willingness-to-pay for this improvement, as shown in Equation 2.7. We use the undiscounted version of fuel savings to avoid complicating matters unnecessarily. If we assume fuel economy and annual driving to be fixed over the ownership period and fuel prices to follow a random walk, the only difference between the discounted and undiscounted versions of fuel savings lies in one parameter that is a geometrical sum of interest rates over the ownership period. Thus, we will need to make an additional assumption on the interest rate. Note that this parameter only scales the underlying relationships between willingness-to-pay and optimal kilometers by a constant but does not alter the direction of this relationship. Substituting

(2.3) into (2.7) and rearranging the terms, we obtain an expression for the optimal distance driven with a car per year, as shown in Equation 2.8.

$$\mathrm{MWTP(FE)} \equiv \left(\frac{1}{\mathrm{FE}} - \frac{1}{\mathrm{FE}+1}\right) \times \mathrm{FP} \times \mathrm{Km/T} \times \mathrm{T} \tag{2.7}$$

$$\mathrm{Km/T} = \frac{\frac{\partial \mathbf{p}(\cdot)}{\partial FE} \times FE^2 \times (FE+1)}{\mathrm{FP} \times (2FE+1) \times \mathrm{T}} \tag{2.8}$$

From Equation 2.8, it follows that the demand for driving a car is decreasing in fuel prices and increasing in fuel economy but at a decreasing rate. Thus, consumers who are willing to invest in better fuel economy are those who expect to drive intensively. However, at higher fuel prices, an improvement in fuel economy results in a smaller increase in kilometers driven. All these conditions are summarized below:

$$\frac{\partial \mathrm{Km}}{\partial \mathrm{FP}} < 0 \quad \text{and} \quad \frac{\partial \mathrm{Km}}{\partial \mathrm{FE}} > 0 \quad \text{and} \quad \frac{\partial}{\partial \mathrm{FE}}\left(\frac{\partial \mathrm{Km}}{\partial \mathrm{FE}}\right) < 0 \quad \text{and} \quad \frac{\partial}{\partial \mathrm{FP}}\left(\frac{\partial \mathrm{Km}}{\partial \mathrm{FE}}\right) < 0$$

Without a functional dependency of the price gradient of fuel economy on fuel prices, the computed optimal driving intensity is proportional to changes in fuel prices: if fuel prices double, the driving intensity halves, ceteris paribus. In case the price gradient of fuel economy also varies with fuel prices, the change in optimal driving intensity also depends on the magnitude of the price gradient of fuel economy relative to the (second) derivative of the price gradient of fuel economy with respect to the fuel price. By computing the derivative of optimal kilometers to the fuel price, it can be shown that

$$\frac{\partial \mathrm{Km}}{\partial \mathrm{FP}} < 0 \text{ if and only if } \frac{\partial \mathbf{p}(\cdot)}{\partial \mathrm{FE}} > \frac{\partial}{\partial \mathrm{FP}}\left(\frac{\partial \mathbf{p}(\cdot)}{\partial \mathrm{FE}}\right) \times \mathrm{FP}$$

After rearranging the terms, the last inequality translates into a condition $E_{FP}^{\frac{\partial \mathrm{Price}}{\partial \mathrm{FE}}} < 1$, i.e., the elasticity of the price gradient of fuel economy to fuel prices should be less than one to lead to a decrease in the optimal driving intensity.

Based on the derived optimal driving intensity, we can also compute the total emission of CO_2 (in tons) from a car powered by a specific engine type at a given fuel price as CO_2 emissions (gram/liter) $\times$ fuel economy (km/liter)$^{-1}$ $\times$ Km/T $\times$ 10^{-6}.

Thus, a functional dependency of the total CO_2 emissions on fuel prices reflects that of the total driving intensity, scaled by a factor specific to each car version.

The hedonic prices for product attributes are estimated by regressing the product price on its characteristics. From an econometric point of view, there are two main estimation issues – the decision on relevant product attributes to be included into the hedonic price regression and the choice of its functional form. Theoretically, the equilibrium price function $\mathbf{p}(\cdot)$ may take any form, and the choice of product attributes is usually determined by the data availability, research question, and engineering background of the product. Here, it is important to choose those attributes and, accordingly, a regression specification that supports either the law of diminishing marginal utility for an "economic good" or the law of increasing marginal disutility for an "economic bad". These estimation issues are discussed in detail in the following two subsections after a description of the data.

2.2.2 Data

The data for the investigation comes from a web database provided by the largest automobile club in Germany, ADAC.[5] It gives an overview of vehicle prices, technical and non-technical characteristics of all automobiles available in Germany since the mid-1990s, including the dates (month and year) of the start and the end of each car model's production. We also obtain monthly fuel prices from the ADAC database and merge them to the car description data. All monetary values in the dataset have been inflation-adjusted by using the consumer price index (CPI), which is normalized to one in April 2010. Fuel prices are also seasonally adjusted using X-12 ARIMA – a model that is used by both the US Census Bureau and German Federal Statistical Office.

In our estimation, we focus on the period of three years and analyze how the market value of fuel economy responds to fluctuations in fuel prices over the period from 2011 to 2013. For this period, we additionally retrieve values of new passenger car registrations per year from the German Federal Motor Transport Authority (Kraftfahrtbundesamt[6]). To avoid an influence of outlier values, we select only those car models that have more than 50 units in the new passenger car registrations per year. A car model is defined by HSN-TSN code and transmission type (e.g., manual). The HSN and TSN stand for producer (Herstellerschlsselnummern) and type (Typschlsselnummern) key codes, respectively, which are set by the German Federal Motor Transport Authority. The HSN-TSN code uniquely identifies a car

[5]http://www.adac.de/infotestrat/autodatenbank/default.aspx.
[6]http://www.kba.de

by its model name (e.g., VW Golf), car body type (e.g., hatchback), production start date (e.g., 01/July/2001), engine size (e.g., 1997 cm^3), horsepower (e.g., 125 HP), and fuel type (e.g., diesel). In our analysis, we consider only car models with gasoline or diesel engines. Vehicles with other engine types constitute a tiny fraction of new car registrations (less than 2%). Our focus also lies on passenger cars from compact and middle classes and with sedan, hatchback, and station wagon body types. The selected car types cover on average 71% and 68% of the sales in the compact and middle classes, respectively. The rationale behind selecting these vehicles lies in their popularity among car buyers and, thus, the well developed supply of different combinations of product attributes. Hence, the selected car classes should represent the market and average technological patterns best.

The data in ADAC are highly disaggregated – two versions of the same product defined by the HSN-TSN code and transmission type are recorded separately if they differ in optional features not included in the baseline version of a car. These optional features lead to higher prices of a car model without altering car performance and fuel economy and hence do not help explain the relation between fuel economy and vehicle prices. As the main intention of this paper is to gain a monetary value for fuel economy, we therefore perform our analysis for a baseline version of each product determined by the lowest product price.[7]

A benefit of estimating implicit prices for product attributes based on the ADAC data is that this source provides a spectrum of all available products on the market over the whole period of investigation. Thus, all technological changes in the whole vehicle supply and their corresponding prices are observed. The price information for cars is represented by the Manufacturer Suggested Retail Price (MSRP), also known as the list price. Determined by the manufacturers, this price intends to provide a standard for the pricing of a product based on its characteristics. Hence, the MSRP reflects the manufacturer's assessment of the consumer's tastes for vehicle attributes in general. In our analysis, we look at the variation in car prices of similar car specifications due to the differences in fuel prices at the time of market entry. At this stage, possible car rebates and differences in the bargaining power between sellers and buyers are irrelevant factors.

2.2.3 Selection of car attributes

For empirical applications of the hedonic price model, it is important to decide what product attributes the regression should entail to appropriately explain the

[7] Tables 2.8 and 2.9 give an overview of the selected models for gasoline and diesel cars, respectively, with the number of products and the average vehicle prices.

relationship between the price of a good and its characteristics. The model-building strategy in terms of the variable selection technique in this paper is based on the engineering background of the automotive industry, the quality of the available data, the car characteristics that are cited as important for buyers in industry overview reports[8] and that have been used in previous studies, and various statistical criteria for a model fit (e.g., C_p, information criteria, and Adjusted R^2).

The primary focus of this paper is the parameter estimate for fuel economy used in a subsequent analysis. The ADAC data provide three measures of fuel economy – city, highway, and weighted-average among city and highway values. In this paper, the latter measure is considered. From a technological perspective, however, fuel economy is strongly related to other car characteristics. This interdependence leads to a multicollinearity problem and, thus, to highly unstable parameter estimates and imprecisely estimated implicit prices. To overcome the strong interdependence between car attributes, many authors have proposed to include a variable that represents only one aspect of either fuel economy or vehicle performance (e.g., Agarwal and Ratchford, 1980). For example, Uri (1988) advises against any inclusion of the fuel economy variable, whereas Gramlich (2008) includes two different specifications of the fuel efficiency - miles per gallon (MPG) as a proxy for all other ("negative") product qualities ("higher MPG is strongly associated with lower other quality", p. 7) and the price of fuel divided by miles per gallon ($PM) as a measure of fuel economy itself. The present paper, however, undertakes another approach. Following the engineering literature, in which one may find a value of a power-specific fuel consumption (e.g., Van den Brink and Van Wee, 2001; Sprei et al., 2008), this paper considers a measure of fuel efficiency that is defined as a product of fuel economy with some indicator of a car's performance. In general, fuel efficiency refers to the amount of fuel necessary to produce a useful service output (Patterson, 1996). A better value of fuel efficiency means that less fuel is needed for the same amount of output. Service output in the car example can be represented by various variables for car performance (e.g., horsepower, kW, power output per liter, etc.). In this paper, we follow previous studies and define fuel efficiency as a product of fuel economy and horsepower.[9] This measure allows us to control for car performance while recovering the relationship between vehicle prices and fuel economy of a theoretically plausible direction. As can be seen in Table 2.1, the fuel economy of vehicles increases over model years but has a negative correlation with car prices, as shown in Table 2.2. We also see that fuel economy is highly correlated with various measures of car performance and engine characteristics. Advocated from a technology perspective, this pattern reflects

[8] The industry overview reports can be found, for example, at http://www.dat.de.

[9] Other measures of car performance are highly correlated with horsepower and consequently yield statistically similar estimation results.

the fact that heavier and more powerful cars cost more but also consume more fuel. Adjusted by the car performance, however, the expected positive relationship between the vehicle price and fuel economy is restored.

Table 2.1: Fuel prices, car prices, and fuel efficiency over years

		Diesel			Gasoline		
		2011	2012	2013	2011	2012	2013
Fuel price	Mean	1.39	1.42	1.34	1.50	1.54	1.47
	SD	0.03	0.04	0.02	0.01	0.03	0.02
Car price	Mean	29321.87	28485.04	28212.85	27352.10	27692.72	26572.58
	SD	6936.29	6646.43	6253.51	7992.11	8287.36	7956.5
Fuel economy	Mean	19.99	21.18	21.51	14.97	15.64	16.71
	SD	2.51	2.75	3.26	1.93	2.01	2.32
Fuel efficiency	Mean	2867.51	3017.62	3148.05	2369.69	2529.35	2682.21
	SD	595.79	681.83	711.78	562.56	681.34	667.31
Forced induction	Mean	1	1	1	0.71	0.75	0.86
	SD	0	0	0	0.46	0.43	0.35
N		217	233	231	177	228	227

NOTE: Fuel prices are in 2010 € per liter; car prices are in 2010 €; fuel economy is in km/l. Fuel efficiency is defined as (fuel economy × horsepower). Values for forced induction are shares of the technology within all cars started being produced in a particular model year based on the ADAC data.

On average, diesel cars consume less fuel per unit distance than otherwise comparable gasoline vehicles. For example, a car from the compact class with 140 HP and manual transmission consumes, on average, 6.26 liter of fuel per 100 kilometers ($\equiv$ 16.17 km/l) in the case of a gasoline engine and only 4.93 l/100 km ($\equiv$ 20.51 km/l) with a diesel engine. However, the fuel efficiency of gasoline cars might be significantly improved by the use of forced induction in form of a turbocharger or a supercharger – a gasoline car with similar characteristics but with forced induction achieves 18.31 km/l, an improvement of 13%. The new technology also increases the price of a car. Without accounting for forced induction, gasoline cars are cheaper than diesel cars, but both types are priced similarly when they feature forced induction (Table 2.3). This phenomenon can be explained by the relative novelty of this technology applied to gasoline engines compared to diesel engines and by a relative gain in a car power under forced induction. Despite a relatively higher vehicle price, the share of gasoline cars with forced induction in the supply as a whole has been increasing over time. This finding leads to the conclusion that consumers might progressively value this technology.

Table 2.2: Correlation coefficients for a subset of vehicle attributes

	Price	FC	FE	FEff	HP	Displ	Weight
Car price, 2010 €	1	0.29	-0.26	0.67	0.79	0.76	0.70
Fuel consumption, l/100km	0.29	1	-0.97	-0.20	0.52	0.23	0.21
Fuel economy, km/l	-0.26	-0.97	1	0.23	-0.48	-0.19	-0.20
Fuel efficiency	0.67	-0.20	0.23	1	0.72	0.67	0.34
CO_2 emissions, g/km	0.39	0.96	-0.93	-0.12	0.56	0.37	0.38
Performance Characteristics							
Horsepower (metric)	0.79	0.52	-0.48	0.72	1	0.74	0.44
Power, kW	0.79	0.52	-0.48	0.72	1	0.74	0.44
Acceleration, seconds	-0.69	-0.32	0.31	-0.74	-0.87	-0.61	-0.24
Speed maximum, km/h	0.76	0.36	-0.34	0.76	0.91	0.65	0.35
Engine Characteristics							
Displacement, cm^3	0.76	0.23	-0.19	0.67	0.74	1	0.55
Fuel Type (Gasoline = 1)	-0.10	0.69	-0.70	-0.34	0.19	-0.26	-0.30
Forced induction (“yes”= 1)	0.30	-0.29	0.29	0.39	0.18	0.08	0.26
Transmission (Automatic = 1)	0.36	0.21	-0.22	0.12	0.25	0.24	0.20
Size Characteristics							
Weight, kg	0.70	0.21	-0.20	0.34	0.44	0.55	1
Length, cm	0.49	0.19	-0.20	0.15	0.26	0.31	0.71
Width, cm	0.36	0.15	-0.14	0.13	0.21	0.19	0.63
Height, cm	-0.28	0.07	-0.09	-0.41	-0.30	-0.21	0.13

NOTE: Reported are the Pearson correlation coefficients for continuous variables and the tetrachoric correlation coefficients for dichotomous variables. All values are statistically significant, with the $p < 0.01$ unless otherwise stated; fuel efficiency is defined as (fuel economy × horsepower).

2.2.4 Hedonic price specifications

In a specification of the hedonic price regression presented in Equation 2.9, we allow the coefficient for fuel efficiency to vary with fuel price (FP). Because car makes can react and adjust their car offerings differently depending on the fuel price, we also interact the coefficient for fuel efficiency with an indicator variable for car make, $I(\text{Make}_j = m)$. The assumed double-log functional dependency between car prices and attributes is in line with previous studies that argue that the price differences associated with product- and brand-level variables are best represented as percentage differences rather than absolute differences (Triplett, 1969; Murray and Sarantis, 1999).

$$\begin{aligned}\ln \text{Price}_{jt} = {} & \alpha_1 + \alpha_2 \ln \text{FP}_t \\ & + \Big(\beta_{1m} + \beta_{2m} \ln \text{FP}_t\Big) \times \Big[\ln \text{Fuel Efficiency}_{jt} \cdot I(\text{Make}_j = m)\Big] \\ & + \gamma' X_{jt} + \tau_t + \mu_j + \varepsilon_{jt}\end{aligned} \tag{2.9}$$

Observed vehicle attributes in X_{jt} include a logarithm of total admissible car weight ($\ln$ Weight) and indicator variables for the displacement group, transmission

Table 2.3: Descriptive statistics for the chosen vehicle attributes

		Diesel	Gasoline		
		FI	FI	no FI	WA
Car Price, 2010 €	Mean	28659.37	28802.55	21597.06	27195.00
	SD	6618.12	7792.90	6460.56	8089.06
Fuel Consumption, l/100 km	Mean	4.88	6.40	6.59	6.44
	SD	0.69	0.99	0.78	0.95
Fuel Economy, km/l	Mean	20.91	15.97	15.39	15.84
	SD	2.93	2.32	1.75	2.22
Horsepower	Mean	146.44	174.51	130.75	164.75
	SD	37.12	54.04	40.29	54.41
Fuel Efficiency	Mean	3014.03	2698.83	1984.83	2539.54
	SD	675.04	600.97	525.44	655.91
Displacement, cm^3	Mean	1906.12	1710.19	1729.04	1714.40
	SD	306.18	387.64	399.34	390.04
Weight, kg	Mean	2045.93	1969.98	1880.94	1950.12
	SD	148.92	157.19	126.81	155.35
Automatic (0/1)	Mean	0.41	0.41	0.31	0.39
	SD	0.49	0.49	0.46	0.49
Compact class (0/1)	Mean	0.49	0.50	0.70	0.55
	SD	0.50	0.50	0.46	0.50
Middle class (0/1)	Mean	0.51	0.50	0.30	0.45
	SD	0.50	0.50	0.46	0.50
Number of observations		681	491	141	632

NOTE: "FI", "No FI", and "WA" stand for "forced induction", "no forced induction", and "weighted averages", respectively.

type (automatic or manual), forced induction, and car class (compact or middle). Displacement enters the hedonic price function as a dichotomous variable with five categories ("$\leq$ 1399"; "1400-1999"; "2000-2499"; "2500-2999"; and "$\geq$ 3000" cm^3). Displacement is taken as a categorical variable to overcome a potential problem due to its high correlation with fuel efficiency and because its distribution in the data is highly discrete. We also include year fixed effects, τ_t, to account for temporal changes in product qualities and make fixed effects, μ_j, to control for unobservable car brand qualities, such as reliability, premium status, and other make-specific features that are constant over time.

We estimate the hedonic price regression by ordinary least squares and cluster standard errors at the make level to account for a potential correlation of observations for cars belonging to the same make. The whole analysis is accomplished for two engine types (diesel and gasoline) separately while pooling the data over both time and car classes. The effects are identified by using variations in product attributes, vehicle prices, and fuel prices at various points at the time of market entry.

For the analysis, we make several assumptions. First, we must assume the equal availability of all cars on the German market. Second, fuel prices can be assumed either to follow a random walk or to be a specific function of historical value realizations. We follow previous studies and assume the former case[10] (Anderson et al., 2013, Langer and Miller, 2013). Thus, the best prediction of future fuel prices in each car entry time is the current fuel price. To check the null hypothesis that fuel prices follow a random walk, we employ a statistical test based on Dickey and Fuller (1979). The data produce test statistics of -1.99 for diesel and -2.74 for gasoline, which do not exceed the 5% critical value of -2.86 in absolute value. Thus, we fail to reject the null hypothesis that fuel prices follow a random walk.

2.3 Empirical Results

In this section, first, the overall model fit and parameter estimates are presented and discussed; second, the estimated effects of fuel prices on the market value of fuel economy, driving intensity, and total CO_2 emissions are discussed.

[10] We additionally estimated the hedonic price regression with the fuel price being various functions of historical realizations. We did not find any statistically significant differences from the results presented in this paper.

2.3.1 Model fit and parameter estimates

At this stage, the vehicle prices are regressed on the selected product attributes, controlling for the make and year fixed effects for each engine type separately. Table 2.4 provides the parameter estimates and model fit for the hedonic price specification. The results indicate that the variation in prices among various car models could be well explained by the controlled physical car characteristics (adjusted-R^2 is between 83-85% without [not shown] and 93-95% with year and make fixed effects).

In the double-log hedonic price specification, the regression coefficients for continuous car attributes correspond to price elasticity – they show a percentage change in the price associated with a percentage change in the attribute value. The main effect of fuel price on car prices is negative but statistically significant only for diesel vehicles. If a car make offers better fuel economy, the drop in the car prices decreases as the derivative of the car price with respect to the fuel price is less negative due to the positive interaction term.

The parameter estimates for dichotomous product attributes show a difference in prices between an attribute level and its reference level, ceteris paribus. The coefficient (say, α) for a dummy variable in the model with a log-transformed dependent variable shows the $(\exp(\alpha) - 1) \times 100$ – percent change in the prices compared to the reference category. Overall, the estimation results are in line with expectations – the vehicle attributes that are generally linked to better quality have significantly positive market values, and vice versa. For example, the estimates for transmission are consistent with observations that cars with an automatic transmission are more expensive than those with a manual one – the coefficient indicates a difference of 6%. A similar logic is applied to the estimates for displacement groups, with larger displacement resulting in higher car prices (on average, 12-16% depending on the fuel type). After controlling for all differences in car attributes for a car with gasoline engine, forced induction does not contribute significantly to the car price variation. This finding means that the higher observed vehicle price shown in the descriptive statistics in Table 2.3 can be fully explained by an increase in horsepower and a consequent improvement in fuel efficiency compared to gasoline cars without forced induction. For diesel vehicles, the parameter for forced induction is not estimated because all diesel cars in the dataset are turbo-charged. Parameter estimates for fuel efficiency and its interaction with fuel prices for each car make are discussed in the next section.

Table 2.4: Parameter estimates for hedonic price regression

	Diesel		Gasoline	
Parameter	Estimate	SE	Estimate	SE
Intercept	5.435*	2.733	-0.612	3.407
lnFP	-16.248**	6.444	-6.595	6.738
(lnFuelEfficiency)	-0.438	0.251	0.038	0.369
(lnFuelEfficiency)× Make Audi	0.019	0.046	-0.038	0.056
(lnFuelEfficiency) × Make BMW	0.066*	0.037	-0.027	0.072
(lnFuelEfficiency) × Make Chevrolet	0.134***	0.028	*NA*	
(lnFuelEfficiency)× Make Citroen	0.345***	0.067	*NA*	
(lnFuelEfficiency)× Make Fiat	0.126**	0.055	*NA*	
(lnFuelEfficiency)× Make Ford	0.059**	0.023	-0.131	0.102
(lnFuelEfficiency)× Make Hyundai	-0.092	0.059	*NA*	
(lnFuelEfficiency)× Make Mazda	0.148***	0.034	-0.250***	0.069
(lnFuelEfficiency)× Make Mercedes	0.123**	0.053	0.113**	0.046
(lnFuelEfficiency)× Make Opel	0.007	0.037	*0.035*	0.116
(lnFuelEfficiency)× Make Peugeot	0.172**	0.073	*NA*	
(lnFuelEfficiency)× Make Renault	0.258***	0.058	*NA*	
(lnFuelEfficiency)× Make SEAT	0.276***	0.025	-0.186***	0.04
(lnFuelEfficiency)× Make Skoda	0.201***	0.031	0.097	0.077
(lnFuelEfficiency)× Make VW	0.048	0.039	-0.043	0.063
(lnFuelEfficiency)× Make Volvo	*Reference*		*Reference*	
(lnFuelEfficiency)×ForcedInduction	*NA*		0.097	0.064
lnFP×(lnFuelEfficiency)	2.084**	0.801	0.784	0.871
lnFP×(lnFuelEfficiency)× Make Audi	-0.049*	0.024	-0.007	0.022
lnFP×(lnFuelEfficiency)×Make BMW	-0.134***	0.03	0.001	0.022
lnFP×(lnFuelEfficiency)×Make Chevrolet	-0.042**	0.017	*NA*	
lnFP×(lnFuelEfficiency)×Make Citroen	-0.137***	0.035	*NA*	
lnFP×(lnFuelEfficiency)×Make Fiat	0.012	0.028	*NA*	
lnFP×(lnFuelEfficiency)×Make Ford	0.004	0.013	0.173***	0.017
lnFP×(lnFuelEfficiency)×Make Hyundai	0.193***	0.04	*NA*	
lnFP×(lnFuelEfficiency)×Make Mazda	0.086*	0.047	0.318***	0.041
lnFP×(lnFuelEfficiency)×Make Mercedes	-0.253***	0.059	-0.103**	0.042
lnFP×(lnFuelEfficiency)×Make Opel	0.005	0.014	0.086**	0.033
lnFP×(lnFuelEfficiency)×Make Peugeot	-0.018	0.024	*NA*	
lnFP×(lnFuelEfficiency)×Make Renault	0.156***	0.033	*NA*	
lnFP×(lnFuelEfficiency)×Make SEAT	-0.014	0.017	-0.002	0.055
lnFP×(lnFuelEfficiency)×Make Skoda	-0.187***	0.023	-0.198***	0.031
lnFP×(lnFuelEfficiency)×Make VW	0.083***	0.024	0.164***	0.036
lnFP×(lnFuelEfficiency)×Make Volvo	*Reference*		*Reference*	
Displacement (1400 - 1999 cm^3)	0.064	0.039	0.036*	0.018
Displacement (2000 - 2499 cm^3)	0.120**	0.043	0.133**	0.045
Displacement (2500 - 2999 cm^3)	0.128***	0.042	0.153***	0.041
Displacement ($\geq$3000 cm^3)	*NA*		0.007	0.065
lnWeight	1.071***	0.112	1.412***	0.167
Compact Class	-0.121***	0.022	-0.098***	0.029
Middle Class	*Reference*		*Reference*	
Automatic Transmission	0.080***	0.008	0.063***	0.011
Forced Induction	*NA*		-0.754	0.469
Year dummies?	Yes		Yes	
Make dummies?	Yes		Yes	
Model Pr>F	< 0.0001		< 0.0001	
Number of Observations	646		510	
Number of Clusters	16		10	
Adjusted R^2	0.9266		0.9493	

NOTE: This table shows the estimation results for the hedonic price regression, where the dependent variable is ln (Car Price). All monetary values are in 2010 €. Standard errors (SE) are heteroskedasticity-consistent and clustered at the make level. The reference category is Volvo, middle class, model year 2013, manual transmission, and displacement "0-1399 cm^3". "NA" stands for "Not Applicable". *p<0.1; **p<0.05; ***p<0.01.

2.3.2 Market value of fuel economy

To compute the market value of fuel economy (FE), note that for fuel efficiency, ln(Fuel Efficiency) = ln(Fuel Economy × Horsepower) ≡ ln(Fuel Economy) + ln(Horsepower) holds. Hence, the derivative of the price with respect to fuel economy does not depend on the performance value, and for each make, it is computed as in Equation 2.10, with standard errors computed as in Equation 2.11.

$$\frac{\partial \text{Price}}{\partial \text{FE}} = \left[\left(\beta_{1m} + \beta_{2m} \ln \text{FP}\right) \cdot I(\text{Make}_j = m)\right] \times \frac{1}{\text{FE}} \times \text{Price} \tag{2.10}$$

$$SE\left(\frac{\partial \text{Price}}{\partial \text{FE}}\right) = \left[SE\left(\beta_{1m} + \beta_{2m} \ln \text{FP}\right) \cdot I(\text{Make}_j = m)\right] \times \frac{1}{\text{FE}} \times \text{Price}, \tag{2.11}$$

where

$$SE\left(\beta_{1m}+\beta_{2m} \ln \text{FP}\right) = \left[Var(\beta_{1m})+Var(\beta_{2m})\times(\ln \text{FP})^2+2Cov(\beta_{1m},\beta_{2m})\times(\ln \text{FP})\right]^{1/2}$$

The market value of fuel economy thus depends on levels of the attribute, car price, and fuel price at which it is computed. Because car makes might differently adjust their car offerings to the fuel price fluctuations, the coefficient for fuel efficiency in the price regression is interacted with an indicator variable for car make. Thus, the market value of fuel economy also varies by car make. Table 2.5 gives an overview of these values for the investigated car makes of two engine types along with the standard errors computed at the median values of car prices and fuel economy for each type of vehicle and at the fuel price of 1.50 €/l (the average fuel price for both engines over the investigated period). Because values of the price gradient with respect to fuel economy are directly proportional to the vehicle price and inversely proportional to the attribute value, as the value of the price gradient increases, the potential for improvement in the attribute value increases because the market still values such improvements relatively highly. The percentage change in the vehicle price due to a 1% change in the fuel economy allows a direct comparison of the market values across different vehicles. On average, an improvement in diesel fuel economy is valued more than that for gasoline vehicles in both absolute and relative terms. Differences in values among car makes can be explained by adjustments in the supply to changes in the fuel price. Because car manufactures allocate their resources to the development of fuel economy and other car attributes differently, consumers face constraints to find a car of each possible realization of attribute bundles by a specific car make.

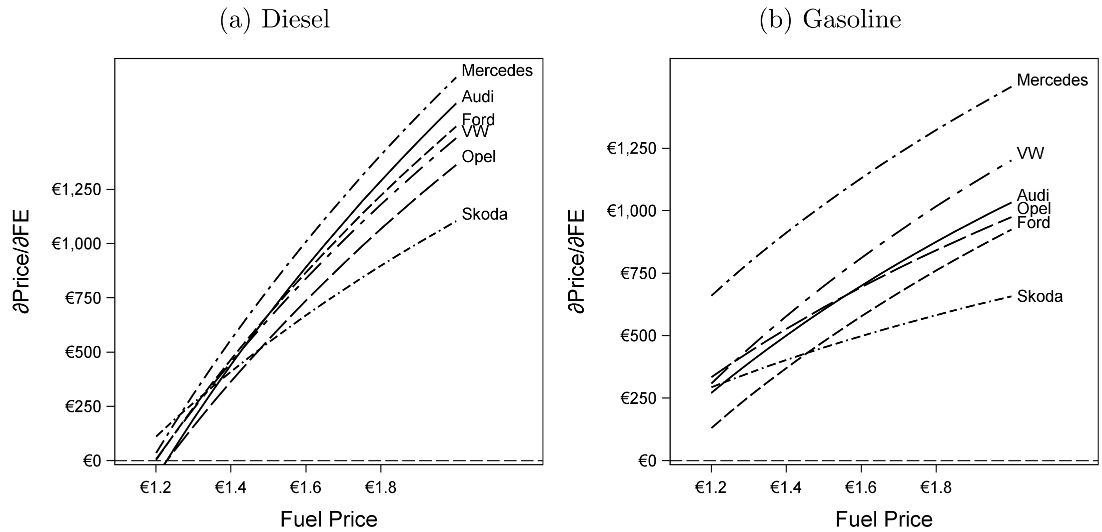
Table 2.5: Market value of fuel economy (km/l)

Diesel				Gasoline			
Make	N obs	€-Δ (1 km/l)	%-Δ (1% FE)	Make	N obs	€-Δ (1 km/l)	%-Δ (1% FE)
Audi	62	674.92	0.41	Audi	77	604.34	0.31
		(99.85)	(0.06)			(139.00)	(0.07)
BMW	61	645.70	0.42	BMW	80	732.30	0.33
		(87.51)	(0.06)			(173.07)	(0.08)
Chevrolet	26	602.02	0.52	Ford	65	477.94	0.29
		(109.92)	(0.10)			(160.00)	(0.10)
Citroen	16	762.88	0.70	Mazda	26	362.99	0.23
		(38.62)	(0.04)			(53.96)	(0.03)
Fiat	16	587.42	0.54	Mercedes	21	1025.36	0.43
		(62.60)	(0.06)			(97.57)	(0.04)
Ford	66	674.57	0.47	Opel	68	613.85	0.43
		(101.99)	(0.07)			(146.78)	(0.10)
Hyundai	17	407.34	0.39	SEAT	23	206.97	0.17
		(71.73)	(0.07)			(77.70)	(0.06)
Mazda	16	820.11	0.59	Skoda	41	452.86	0.37
		(88.47)	(0.06)			(73.15)	(0.06)
Mercedes	28	791.95	0.43	VW	74	699.24	0.38
		(78.81)	(0.04)			(118.95)	(0.06)
Opel	71	558.29	0.42	Volvo	35	746.43	0.36
		(78.27)	(0.06)			(140.40)	(0.07)
Peugeot	30	666.28	0.57			⊘ =592.23	⊘ =0.33
		(41.95)	(0.04)			(118.06)	(0.07)
Renault	23	716.08	0.73				
		(50.15)	(0.05)				
SEAT	24	799.02	0.68				
		(105.19)	(0.09)				
Skoda	30	545.04	0.53				
		(82.03)	(0.08)				
VW	79	653.32	0.49				
		(73.65)	(0.06)				
Volvo	81	599.38	0.41				
		(117.35)	(0.08)				
		⊘ =656.52	⊘ =0.52				
		(80.51)	(0.06)				

NOTE: "€-Δ (1 km/l)" refers to the euro change in the car price if fuel economy changes by 1 km/l and is computed based on Equation 2.10 at the median values for fuel economy and car prices for each car make and at the fuel price of 1.50 €/l for both fuels. "%-Δ (1% FE)" refers to the percentage change in the vehicle price if fuel economy changes by 1%. In parenthesis are standard errors computed as in Equation 2.11. ⊘ denotes the average value over all car makes.

The resulting values for the price gradient of fuel economy as a function of fuel price are depicted in Figure 2.1 for each engine type. Here, only a subset of car makes is presented in order to reduce clutter in the figure. The rationale behind the figures is as follows. First, a positive slope of the dependency means that under increasing fuel prices, the market value of a given fuel economy increases. Second, the steepness of the curves indicates how sensitive the market values are to changes in fuel prices. With increasing fuel prices, the market values improvements in the fuel economy of diesel vehicles more than those of gasoline ones. This phenomenon can be explained by relatively high shares of diesel vehicles on the German car market. Both car manufacturers and consumers have shifted their preferences to diesel vehicles over the last ten years: production shares and market shares of diesel vehicles have been rapidly increasing in this period. Thus, manufacturers had to build necessary capacities to react more quickly to changing fuel prices by improving the fuel economy of each subsequent car generation. In the gasoline car market, consumers are potentially not as concerned with fuel economy as those in the diesel car market, but instead focus on other performance characteristics. Additionally, car manufacturers may not have developed necessary technologies to improve the fuel economy of gasoline vehicles in response to increasing fuel prices as rapidly as in the diesel vehicle market.

Figure 2.1: Market value of fuel economy (km/l) as a function of fuel prices



NOTE: This figure presents the values for the price gradient with respect to fuel economy as a function of fuel prices. The price gradient is computed at the median values for fuel economy and vehicle prices for each type of vehicles based on Equation 2.10.

An elasticity measure helps to better illustrate how rapidly the market value of fuel economy changes with fuel prices. It is computed as in Equation 2.12:

$$E_{FP}^{\frac{\partial \text{Price}}{\partial \text{FE}}} = \frac{\partial\left(\frac{\partial \text{Price}}{\partial \text{FE}}\right)}{\partial \text{FP}} \times \frac{FP}{\left(\frac{\partial \text{Price}}{\partial \text{FE}}\right)} \tag{2.12}$$

Table 2.6 presents average elasticity values for three values of fuel prices, corresponding to the average diesel price of 1.40 €/l, the average gasoline price of 1.50 €/l, and the highest fuel price of 1.60 €/l for the period under investigation. According to our model, the elasticity varies with the fuel price at which it is computed. On average, the elasticity is greater than unity, suggesting that the price gradient of fuel economy changes more relative to the changes in fuel prices. We observe that with increasing fuel prices, the elasticity value substantially drops for both engine types. Thus, the market values improved fuel economy at a diminishing rate.

Table 2.6: Elasticity of $\frac{\partial \text{Price}}{\partial \text{FE}}$ to fuel prices

Fuel Price	Diesel	Gasoline
1.4	5.93	3.54
	(5.74; 6.13)	(3.26; 3.81)
1.5	4.14	2.74
	(4.05; 4.24)	(2.58; 2.90)
1.6	3.25	2.28
	(3.19; 3.31)	(2.17; 2.40)

NOTE: Average elasticity values for the price gradient of fuel economy with respect to fuel prices are presented. The values are computed as in Equation 2.12.

2.3.3 Optimal driving intensity and total CO_2 emission

Given the estimated market values of fuel economy, we compute the underlying optimal annual kilometers based on the assumption of utility-maximizing consumers discussed in the Section 2.2.1. We use Equation 2.8 and plug in the derived formula for the price gradient of fuel economy from Equation 2.10:

$$\text{Km/T} = \frac{\left[\left(\beta_{1m} + \beta_{2m} \ln \text{FP}\right) \cdot I(\text{Make}_j = m) \times \frac{1}{\text{FE}} \times \text{Price}\right] \times FE^2 \times (FE + 1)}{\text{FP} \times (2FE + 1) \times \text{T}}$$

The driving intensity is increasing in fuel economy and car price, i.e., $\frac{\partial \text{Km}}{\partial \text{FE}} > 0$ and $\frac{\partial \text{Km}}{\partial \text{Price}} > 0$. Thus, consumers who are willing to invest more in fuel economy are those who should also expect to drive more. Table 2.7 gives an overview of the implied optimal driving intensity from the computed market value of fuel economy evaluated at the fuel price of 1.50 €/l. This table also provides values for total emissions of CO_2 (tons) from a car powered by a specific engine. The total emissions of CO_2 in tons at a given fuel price are computed as CO_2 emission (gram/liter) × fuel economy (km/liter)$^{-1}$ × Km/T × 10^{-6}.

Table 2.7: Optimal driving intensity (in km/year) and total CO_2 emissions (in tons/year)

Diesel			Gasoline		
Make	Km/year	Total CO_2	Make	Km/year	Total CO_2
Audi	16655.49	2.12	Audi	12456.68	1.73
BMW	18104.49	2.16	BMW	13252.29	1.97
Chevrolet	14856.57	1.89	Ford	8509.84	1.26
Citroen	18448.17	2.37	Mazda	4806.61	0.74
Fiat	12374.74	1.71	Mercedes	15999.16	2.45
Ford	14210.75	1.96	Opel	9214.67	1.41
Hyundai	10479.75	1.31	SEAT	5451.50	0.73
Mazda	20238.55	2.57	Skoda	9138.87	1.23
Mercedes	19543.49	2.49	VW	11837.08	1.78
Opel	12221.20	1.65	Volvo	12394.12	1.90
Peugeot	17886.50	2.18	⊘	10306.08	1.52
Renault	20991.14	2.45			
SEAT	22403.25	2.67			
Skoda	15282.06	1.82			
VW	16122.57	2.05			
Volvo	14791.42	1.88			
⊘	16538.13	2.08			

NOTE: The values for optimal driving intensity are computed at the median values for fuel economy and vehicle prices for each type of vehicles and at the fuel price of 1.50 €/l. ⊘ denotes the average value over all car makes.

Based on the estimated market value of fuel economy, the buyers of diesel cars should be those who expect to drive on average 16538 kilometers annually over the assumed 6 years of a car ownership if diesel fuel costs 1.50 €/l on average, while the optimal annual driving intensity for gasoline car buyers is 10306 kilometers under the same conditions. These values are similar to the official statistics on the average car usage in Germany – 18042 for diesel cars and 10652 km for petrol cars in 2013.[11]

The total of CO_2 emissions produced is determined solely by driving intensity and the fuel used by a vehicle. One liter of fuel produces approximately 26.5 and 23.2

[11]Statista Press Release 11.06.2015 – 213/15 (https://www.destatis.de/DE/PresseService/Presse/Pressemitteilungen/2015/06/PD15_213_85.html).

grams of CO_2 per kilometer driven by diesel and gasoline vehicles, respectively.[12] Hence, for diesel cars to be at least as environmentally friendly as gasoline vehicles at a given amount of kilometers, a gain in fuel economy from diesel cars should be at least 1.1037 times the value gained from gasoline ones. Because diesel drivers are characterized by a higher car usage, as shown in Table 2.7, the total CO_2 emissions of are also higher per year on average than for gasoline vehicles. The values suggest that the efficiency gain from diesel vehicles compared to gasoline cars should be respectively larger in order to offset the environmental pollution caused by more intensive car usage by diesel buyers.

Because the hedonic price model evaluates the dependency in vehicle prices from attributes at the equilibrium, the derived optimal annual kilometrage and CO_2 emissions reflect the average market value without accounting for heterogeneity in consumer tastes while containing all possible self-selection into a car type on driving intensity. Essentially, optimal kilometers reflect the utility a consumer attaches to driving a car of a particular fuel economy, after controlling for its performance.

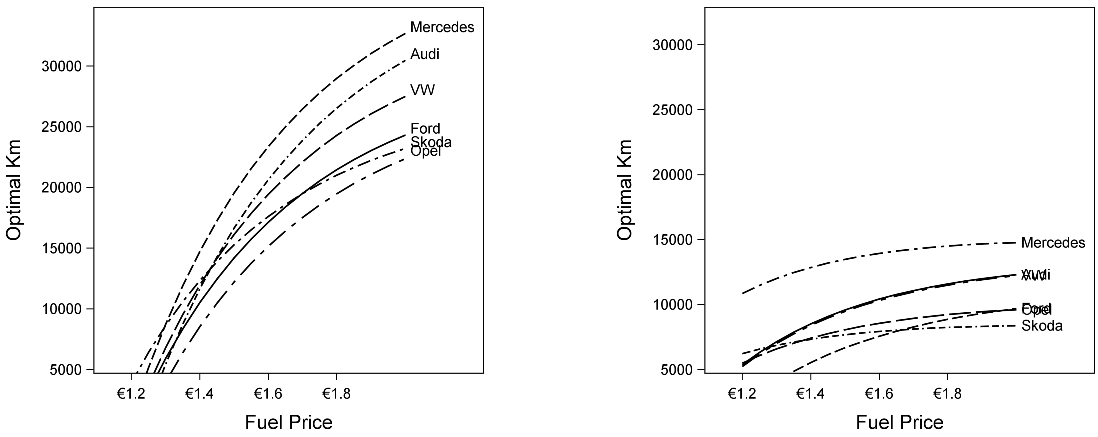
The estimation procedure allows the optimal driving intensity to vary with fuel prices over engine technologies. Without a dependency of the price gradient of fuel economy on fuel prices, the sensitivity of driving would be the same over engine technologies and directly proportional to fuel price changes. Because the elasticity of the price gradient of fuel economy to fuel prices is greater than unity for the estimated fuel price range ($E_{FP}^{\frac{\partial \text{Price}}{\partial \text{FE}}}$, see Table 2.6), the condition for decreasing kilometrage with respect to fuel prices does not hold. A visual presentation of how the derived optimal kilometers vary with the level of fuel prices is given in Figure 2.2. Overall, the derived optimal kilometers are higher for those cars that have better fuel economy and/or higher vehicle prices (to justify the premium paid). Figure 2.3 visualizes a dependency of optimal kilometers on both fuel economy and fuel price. However, with increasing fuel prices, one can increase one's own kilometrage due to a better fuel economy to a lesser degree, as $\frac{\partial}{\partial \text{FP}}\left(\frac{\partial \text{Km}}{\partial \text{FE}}\right) < 0$. Fuel prices will have a negative effect on the driving intensity starting at values denoted as inflection points. Inflection points of a curve show at which level a change in the direction of curvature occurs. On average, fuel prices should be larger than 3.18 €/l for diesel cars and larger than 2.32 €/l for gasoline cars when the utility from driving a car with a better fuel economy becomes smaller than the implied income effect of higher fuel costs on the driving budget.[13]

[12] http://www.kba.de/SharedDocs/Publikationen/DE/Statistik/Fahrzeuge/FZ/Fachartikel/emission_20110315.pdf, p. 6 (accessed: October 08, 2017).

[13] See Table 2.10 for the inflection points for each car make.

Figure 2.2: Optimal driving per year as a function of fuel prices

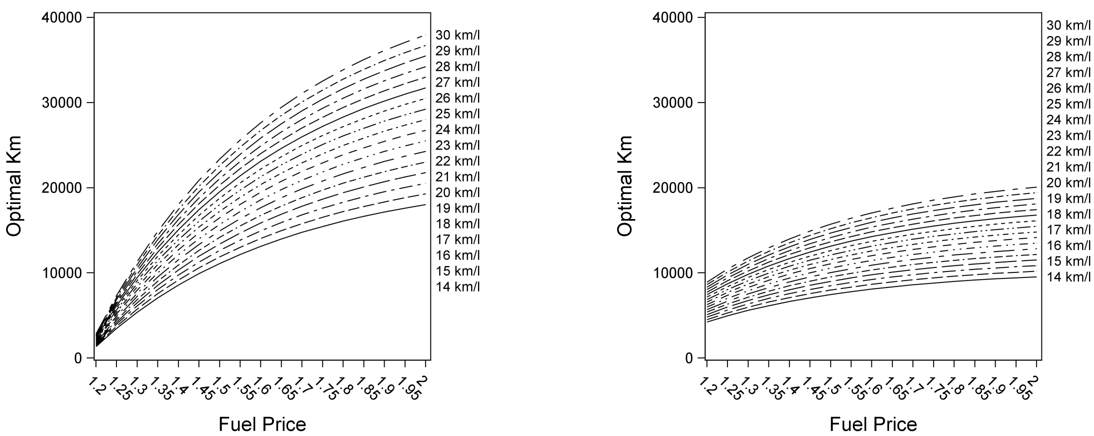
(a) Diesel (b) Gasoline



NOTE: Optimal number of kilometers per year is evaluated at the median values for fuel economy and vehicle prices for each type of vehicles and for the length of car ownership of 6 years.

Figure 2.3: Optimal driving as a function of fuel prices and fuel economy

(a) Diesel (b) Gasoline



NOTE: The figure shows a dependency of the computed optimal number of kilometers per year on fuel prices for different values of fuel economy. With increasing fuel economy, the slope of the curve becomes steeper.

2.4 Discussion and Conclusion

In this section, we summarize the results of our empirical study. In this paper, we aimed to quantify the effects that fluctuations in fuel prices have on the market value of fuel economy. In this line, we considered the value of fuel prices to moderate the value that consumers and manufacturers place on fuel economy, resulting in shifts of car prices' responsiveness to fuel economy. We based our empirical strategy on the hedonic price model, whereby we regressed vehicles' prices on their attributes, including fuel economy and its interaction with fuel price. For this task, we used data on detailed car specifications of frequently sold vehicles from compact and middle classes available on the German market for three subsequent model years (2011–2013). We contrasted price adjustments of a car to its fuel economy with fluctuations in fuel prices over the investigated period. A focus on the German automobile market is justified because this market is characterized by having the biggest car manufacturers in Europe, covering approximately 22% of new passenger car registrations in Europe (as of 2016[14]) and having one of the highest car penetration rates in Europe: 550 vehicles per 1000 inhabitants (as of 2014[15]), which corresponds to 85% of households owning a car (as of 2014[16]).

The methodology applied in this paper enabled us to recover effects that the fuel price has on consumers' willingness-to-pay for improvements in fuel economy, implied optimal car usage, and resulting CO_2 emission values. To compute willingness-to-pay, the values of fuel economy instead of fuel consumption, which is commonly used in Germany, were taken for the analysis. This procedure was done to ensure that the product attributes entered into the regression are in line with the laws of diminishing marginal utility from economic goods. To prevent a problem of severe multicollinearity due to technological interdependence among car attributes, we related fuel economy to car performance (horsepower). This measure also assisted in a direct comparison between different types of engine technologies that differ in the underlying physics.

We found significant differences in the market values of fuel economy between diesel and gasoline vehicles and their responsiveness to changes in fuel prices. Diesel cars were characterized by a larger elasticity of the price gradient of fuel economy to fuel prices compared to gasoline cars. We explain this finding by the relatively higher importance of diesel cars for both consumers and manufacturers on the German automobile market. During recent years, German car manufacturers have shifted their focus to the production of diesel cars, and German consumers have

[14]https://www.statista.com/statistics/246350 (accessed: October 08, 2017).
[15]https://www.statista.com/statistics/607540 (accessed: October 08, 2017).
[16]https://www.statista.com/statistics/516280 (accessed: October 08, 2017).

shifted their interest to purchasing diesel vehicles. This trend is linked to the better average fuel economy of diesel cars compared to gasoline cars and lower diesel fuel price at the pump as a result of favorable fuel taxation of diesel. Thus, diesel drivers might be more sensitive to changes in fuel prices and subsequently to improvements in fuel economy because they have to invest more at the time of car purchase in terms of vehicle prices and the annual car tax they pay for diesel cars compared to gasoline ones.

The recovered high responsiveness of the market value of fuel economy to fuel prices resulted in optimal annual driving intensity, which was an increasing function of fuel prices (but at a diminishing rate). This finding implies that the marginal benefits of driving a car of a specific fuel efficiency were still higher than the corresponding effects of changes in the fuel price on consumers' budget for driving. Additionally, we computed the total CO_2 emissions realized by the recovered optimal driving and find values similar to the official statistics. Since the total amount of carbon dioxide emissions from a vehicle is proportional to the intensity of fuel consumption determined by kilometers driven under a given fuel economy, a decrease in pollution levels can be realized through a reduction in driving intensity and/or an improvement in a car's fuel economy.

The values of CO_2 emissions could alternatively be included into the hedonic price regression instead of fuel economy as a direct target of the environmental policy. However, this specification, while yielding similar results for the market value of fuel economy, will not enable a derivation of the driving intensity. Moreover, fuel prices are directly linked to the consumer's fuel expenditures, along with the values of vehicle fuel consumption. Thus, fuel prices might affect the consumer's willingness-to-pay for marginal improvements in the fuel consumption rather than for marginal improvements in the CO_2 emissions. However, an investigation of which consumer motivations – environmental or financial – are of greater importance when choosing a car was not possible with the data used in this study, as both measures (FC and CO_2) are correlated.

Overall, the paper demonstrated how one can use the hedonic price model to estimate fuel price effects on willingness-to-pay for product attributes on a complex market as automobiles while utilizing the open-source data that are considered to represent an equilibrium outcome between the supply- and demand-side interactions.

While our analysis made full use of the available data, there are several possible extensions to the analysis presented in this paper that cannot be addressed with a help of the data used. By regressing vehicle prices on technological attributes, the current paper assumed that the implied optimal kilometers driven are the same for each consumer, who paid the same price for a car with the same fuel economy value. Accordingly, the results shed light only on the aggregate market behavior. Individual purchase data with real transaction prices and consumer-specific characteristics could be used to account for consumer heterogeneity in their tastes for cars and reactions to fuel prices. However, the current study demonstrated that even in the case of having data solely on product prices and underlying attributes, it is possible to recover plausible values for the considered market outcomes, which are in line with the official statistics.

Additionally, data on used vehicles could enrich the analysis by providing information on the actual driven kilometers and actual fuel consumption for various types of vehicles. Because the official values of fuel consumption might differ from values realized by the vehicle usage, the actual driving behavior can facilitate the investigation of effects that changes in fuel prices would imply for different consumer groups – e.g., what vehicle types would become optimal, given the driving behavior and consumer preferences for attribute bundles. Additionally, a potential asymmetric response to increasing and decreasing fuel prices could be investigated. In general, information on any factor that might influence consumers' car choices and their valuation of product attributes, such as the distributional inequality of products, out-of-stock conditions, advertising, effectiveness of the sales force, and product awareness, could enrich the analysis.

2.5 Appendix

Table 2.8: Overview of car models with a gasoline engine

Make	Model	N products	N observations	Car Price
Audi	Audi A3/RS3/S3	16	33	27348.68
Audi	Audi A4/S4	15	31	35519.69
Audi	Audi A5/S5	6	13	39119.73
BMW	BMW 1	11	31	28356.11
BMW	BMW 3	18	49	37910.25
Ford	Ford Focus	21	34	21107.67
Ford	Ford Mondeo	9	31	30679.04
Mazda	Mazda 3	8	14	20871.79
Mazda	Mazda 6	8	12	27779.27
Mercedes	Mercedes A	3	4	35928.33
Mercedes	Mercedes C	10	17	38010.4
Opel	Opel Astra	20	49	21034.87
Opel	Opel Combo	1	2	16826.53
Opel	Opel Insignia	7	17	32467.06
SEAT	SEAT Exeo	6	6	26421.81
SEAT	SEAT Leon	9	13	21150.37
SEAT	SEAT Toledo	3	4	16913.43
Skoda	Skoda Octavia	20	35	21659.54
Skoda	Skoda Rapid	6	6	16468.11
VW	VW Beetle/New Beetle	4	16	24470.04
VW	VW Caddy	3	4	22215.78
VW	VW Golf	12	22	24940.41
VW	VW Jetta	3	5	26620.96
VW	VW Passat	7	27	34690.65
Volvo	Volvo S60	2	5	32342.57
Volvo	Volvo V40	6	13	27885.18
Volvo	Volvo V60	5	17	37129.09
		$\sum = 27$	$\sum$=510	$\oslash$ =28552.05

NOTE: Number of products is based on the HSN-TSN key in the ADAC data. Car prices are average values over time in 2010 €. $\oslash$ denotes the average value over all car makes.

Table 2.9: Overview of car models with a diesel engine

Make	Model	N products	N observations	Car Price
Audi	Audi A3/RS3/S3	10	18	26834.27
Audi	Audi A4/S4	18	32	35882.13
Audi	Audi A5/S5	6	12	40250.98
BMW	BMW 1	14	24	28341.12
BMW	BMW 3	21	37	38341.1
Chevrolet	Chevrolet Cruze	6	24	23486.41
Chevrolet	Chevrolet Malibu	1	2	29529.3
Citroen	Citroen Berlingo	2	5	21132.24
Citroen	Citroen C4	2	2	21513.22
Citroen	Citroen C5	1	2	29919.58
Citroen	Citroen DS4	2	5	25227.82
Citroen	Citroen DS5	1	2	31200.77
Fiat	Fiat Bravo	1	5	20988.01
Fiat	Fiat Doblo	4	10	20509.83
Fiat	Fiat Sedici	1	1	20739.67
Ford	Ford Focus	12	31	23261.93
Ford	Ford Mondeo	8	35	31423.59
Hyundai	Hyundai i30	6	12	20269
Hyundai	Hyundai i40	3	5	28131.68
Mazda	Mazda 3	4	5	24155.47
Mazda	Mazda 6	7	11	31116.34
Mercedes	Mercedes A	2	2	25275.31
Mercedes	Mercedes C	13	25	39685.7
Mercedes	Mercedes Citan	1	1	20439
Opel	Opel Astra	15	33	23673.7
Opel	Opel Combo	3	4	20160.9
Opel	Opel Insignia	18	34	32344.47
Peugeot	Peugeot 308	7	11	22417.11
Peugeot	Peugeot 508	9	16	29178.61
Peugeot	Peugeot Partner	2	3	20188.92
Renault	Renault Kangoo	4	6	19060.08
Renault	Renault Laguna	4	7	27811.49
Renault	Renault Megane	7	10	22267.05
SEAT	SEAT Exeo	4	10	27439.53
SEAT	SEAT Leon	7	13	24108.41
SEAT	SEAT Toledo	1	1	18845.79
Skoda	Skoda Octavia	15	25	23349.23
Skoda	Skoda Rapid	3	5	17804.01
VW	VW Beetle/New Beetle	2	8	23838.26
VW	VW Caddy	8	17	26975.49
VW	VW Golf	11	24	24826.55
VW	VW Jetta	2	4	26481.39
VW	VW Passat	10	26	35072.11
Volvo	Volvo C30	2	3	25107.27
Volvo	Volvo S40	3	5	28745.35
Volvo	Volvo S60	6	23	32485.13
Volvo	Volvo V40	6	23	27994.56
Volvo	Volvo V60	7	27	34537.24
		$\sum = 48$	$\sum =646$	$\oslash =28865.15$

NOTE: Number of products is based on the HSN-TSN key in the ADAC data. Car prices are average values over time in 2010 €. $\oslash$ denotes the average value over all car makes.

Table 2.10: Inflection point for optimal kilometers as a function of fuel price

Diesel		Gasoline	
Make	FP, €/l	Make	FP, €/l
Audi	3.34	Audi	2.26
BMW	3.29	BMW	2.22
Chevrolet	3.15	Ford	2.65
Citroen	2.85	Mazda	3.23
Fiat	3.15	Mercedes	1.71
Ford	3.26	Opel	2.19
Hyundai	3.43	SEAT	2.79
Mazda	3.11	Skoda	1.66
Mercedes	3.23	VW	2.35
Opel	3.34	Volvo	2.14
Peugeot	3.09	⊘	2.32
Renault	2.95		
SEAT	2.94		
Skoda	3.08		
VW	3.25		
Volvo	3.35		
⊘	3.18		

NOTE: Inflection point of a curve shows level of fuel prices at which a change in the direction of curvature occurs. ⊘ denotes the average value over all car makes.

Chapter 3

On Factors of Consumer Heterogeneity in (Mis)valuation of Future Energy Costs: Evidence for the German Automobile Market[1]

Vlada Pleshcheva, Daniel Klapper, Till Dannewald

Abstract

In this paper, we first recover the individual valuation of expected future fuel costs at the time of a car purchase and then explore how various factors relate to the recovered consumer undervaluation of fuel savings (on average, consumers' willingness-to-pay for a €1 reduction in fuel costs is below €0.20). For this purpose, we use survey data on the individual purchases of new passenger cars in Germany over seven years and use the expected driving intensity and the expected length of car ownership as stated by consumers to construct individual values of the present-discounted fuel costs. We then compare the variation in these values to that in the prices paid by buyers of cars with identical specifications. Individual tastes for car attributes are recovered nonparametrically within a "preference inversion" procedure for diesel and gasoline vehicles of various car classes, controlling for unobservable product attributes, correlations in tastes for car features, and the possibility to deduct a portion of annual fuel costs from taxes. Our results show that consumers' financial ability, education, and stickiness to a previously bought car make as a strategy to reduce choice complexity are the most important determinants of the consumer valuation of future energy costs.

[1]Presented at the internal seminars; the 39$^{\text{th}}$ Annual ISMS Marketing Science Conference, University of Southern California, Los Angeles, 07.-10.06.2017; and the Annual Meeting of the Committee for Industrial Economics, Wirtschaftsuniversität Wien, 22.-23.03.2018.

Keywords: Energy-efficiency paradox; hedonic discrete choice model; vehicle purchase; willingness-to-pay
JEL Classification: D12, D90, M31, Q51.

3.1 Introduction

The literature on consumer valuation of energy-using durable goods has long discussed the trade-off between the higher upfront capital costs of a more efficient product and the potentially lower future operating costs linked to the product's usage over the ownership period (e.g., Hausman, 1979; Dubin and Mcfadden, 1984). Economic theory suggests that a "rational" consumer should be willing to invest upfront in better energy efficiency as much as it allows the consumer to save on the expected operating costs given expectations of energy prices and the intensity of product usage. If, however, a consumer is willing to pay less (more) than these savings, undervaluation (overvaluation) of energy efficiency occurs.

Empirical studies provide mixed evidence on the consumer valuation of the future energy costs and energy efficiency of a product. One stream of research concluded that consumers correctly account for a trade-off between capital costs and operating costs (e.g., Busse et al., 2013; Sallee et al., 2016; Grigolon et al., 2017). Other studies have found that consumers either pay little attention to energy costs when purchasing energy-using durable goods and do not make calculations for future energy savings from a more efficient product (Turrentine and Kurani, 2007; Allcott, 2011) or exhibit certain biases and errors in their valuation (e.g., "MPG Illusion"; Larrick and Soll, 2008). Although extensive financial investments in car purchases should encourage consumers to compare upfront costs and potential savings in future fuel costs, the results of previous studies have been inconclusive regarding the extent to which consumers' car purchase decisions are in line with optimal (cost-minimizing) behavior (see Greene, 2010 and Helfand and Wolverton, 2011 for an overview of the studies).

The present study aims at contributing to this discussion. We first quantify the direction and magnitude of consumers' trade-off between the higher upfront capital costs and the lower ongoing usage costs of a more fuel-efficient car. Second, we explore the role of various consumer- and transaction-specific characteristics in consumers' valuation of future fuel costs. Our investigation is based on a detailed dataset from an anonymous survey of consumers who bought a new car within the previous three months in Germany over a period of seven years. The richness and structure of the data provide several conceptual and methodological advantages for an empirical analysis to obtain insights on factors of consumer heterogeneity in the valuation of future fuel costs.

First, we complement previous research on the consumer valuation of future fuel costs by considering various types of observed consumer heterogeneity during the investigation. In addition to the observed heterogeneity in tastes for car attributes, we incorporate differences in consumers' anticipated driving intensity and length of car ownership. Most previous studies have examined the valuation of energy costs only at the aggregate (market) level while failing to account for consumer heterogeneity at all (e.g., Ohta and Griliches, 1986; Dreyfus and Viscusi, 1995; Allcott and Wozny, 2014), incorporating consumer heterogeneity in tastes for product attributes only through random coefficients within a discrete choice framework (e.g., Berry et al., 1995; Train and Winston, 2007), or controlling for socio-demographic characteristics within a hedonic demand framework (Busse et al., 2013; Fan and Rubin, 2010). Several recent studies have also incorporated differences in consumers' vehicle miles traveled. For example, Grigolon et al. (2017) used a specification of the aggregate random coefficient logit demand model (Berry et al., 1995) that accounts for heterogeneous responses to fuel costs due to consumers' differences in annual mileage. Sallee et al. (2016) used variations in the odometer readings for identical used cars to test whether used vehicle prices move one-for-one with the value of remaining future operating costs, thus identifying the value consumers place on fuel economy after controlling for other attributes. Bento et al. (2012) used a simulation to show that ignoring heterogeneity in consumers' tastes and product usage in empirical analyses can significantly affect the estimated willingness-to-pay values and could be a source of the undervaluation of energy costs highlighted in the previous literature. The current paper differs from these studies in the methodology and data used for identification.[2] In our study, we use information on the length of ownership of previous cars and the expected driving intensity for a new car as stated by the consumers themselves to construct individual values for the present-discounted future fuel costs (PVFC). The values that consumers place on the expected fuel expenses for new vehicles are then identified by comparing the variation in the individual PVFC values with that in the prices paid by buyers of cars with identical specifications. Under the "rational" cost-minimizing behavior principle, the prices paid for cars should move one-to-one with changes in future fuel costs for a given car quality.

Second, the presence of various consumer characteristics linked to choices in the dataset enables the current study to use a method proposed by Bajari and Benkard (2005) that addresses weaknesses of the discrete choice and hedonic demand models

[2] Table 3.20 compares the current study with previous empirical work on consumer valuation of fuel efficiency based on revealed preferences.

– two commonly used estimation approaches when using revealed preference data. One of the methodological advantages of the procedure developed by Bajari and Benkard (2005) (hereafter, the hedonic discrete choice model) is its flexibility. In this model – in contrast to the discrete choice model – the distributions of tastes for product attributes are recovered directly from the data without a need to impose any distributional assumptions (usually from a parametric family). Sonnier et al. (2007), for example, discussed the sensitivity of the evaluated willingness-to-pay values to the different parametrization and prior distributional assumptions within the discrete choice model. Moreover, the hedonic discrete choice model uses only observations for the chosen products without needing to construct choice sets faced by a consumer, which might become extremely difficult for a highly differentiated product category (such as automobiles). Thus, one does not have to make assumptions about consumer search and the sets of the considered products. The exploited estimation method extends the classical Rosen hedonic demand two-step model (Rosen, 1974) by allowing for heterogeneity in the values for consumes' willingness-to-pay for product attributes. The method can also be referred to as a "preference inversion" procedure: it recovers heterogeneous tastes from the utility maximization problem based on estimations of individual implicit prices from the hedonic price function, which serves as a budget constraint for consumers. Bajari and Benkard (2005) showed that the proposed methodology can be applied to markets featuring oligopolistic competition for both continuous and discrete product space, controlling for unobservable product attributes. Thus, the methodology relaxes the assumptions in Rosen (1974) on perfect competition, the continuum of products, and the perfect observability of product attributes. The German automobile industry is well suited for the analysis because it is a well-developed market, with the supply characterized by a large number of car versions offered.

Econometrically, in the first stage, individual tastes for car attributes, including the present-discounted value of fuel costs, are derived by estimating the hedonic price function nonparametrically. In the second stage, heterogeneity in the recovered individual willingness-to-pay values for a reduction in fuel costs is then explored via a regression analysis using the consumer- and transaction-related characteristics as explanatory variables. For this goal, we use the quantile regression method, which allows us to estimate the differential effects of covariates along the conditional distribution (and not only the conditional mean) of the recovered valuation parameter.

In our analysis, we focus on passenger cars with gasoline and diesel engines from six car classes defined by the German Federal Motor Transport Authority. Our sample includes only consumers who bought a car privately. In contrast to corporate car buyers, private buyers should be concerned about a car's operating costs because they will bear these costs themselves in the future. We also control for the possibility that a portion of fuel costs can be deducted from their annual income taxes if the car is used for work or business purposes. We perform the entire investigation of the relationship between purchase prices and future fuel costs separately for diesel and gasoline car buyers. In this way, we control for the problem of consumers' potential selection into a specific type of car. Previous studies have shown that under certain circumstances this selection issue may lead to biased estimation results and has been addressed by studies that jointly estimate vehicle choice and utilization (e.g., Bento et al., 2009; Feng et al., 2013). In our study, we do not model car utilization. We condition consumers' purchase decisions on their anticipated driving. For example, if a consumer expects to drive intensively, s/he might choose a diesel car because it has lower fuel consumption and because diesel fuel prices are lower. However, diesel vehicles are more expensive than gasoline cars. As a result, the consumer faces a trade-off between the upfront costs and the savings in future fuel costs within the car type. Additionally, if consumers are cost-minimizing, they should value a car of a particular engine type as much as it allows savings in ongoing fuel costs. We do not model consumers' choice of a diesel or a gasoline vehicle conditional on the anticipated driving intensity, and this stage of the consumer's decision should not affect the valuation parameters in our setting.

Our estimation results indicate that there is a high degree of undervaluation of potential fuel savings – for a €1 reduction in future fuel costs, the sampled consumers are estimated to be willing to pay no more than €0.20 on average. The estimated willingness-to-pay varies among engine types and car classes, with higher average valuations for higher car classes and for diesel vehicles. The estimates remain robust to specifications under various assumptions, including the time period under investigation, the interest rate, and the length of car ownership.

Our finding of a high level of consumer myopia contrasts to the recent study by Grigolon et al. (2017), who used European data. In their analysis, the authors could not reject the hypothesis of consumers' full valuation of fuel costs. The discrepancy in these results could lie in both the methodologies applied and the characteristics of the dataset used. The estimation in Grigolon et al. (2017) was performed for several European countries and with recent observations that might lead to a higher valuation parameter. Furthermore, the authors included in their estimation the heterogeneity in consumers' driving patterns by drawing from the distribution of the aggregate mileage in the UK. In contrast, we use the expected annual kilometers to be driven with the chosen car as stated by the consumers themselves. Thus, for the sample analyzed in our study, we can directly relate the heterogeneity in mileage to the willingness-to-pay for fuel savings. Methodologically, our study also differs from Grigolon et al. (2017) in that we do not impose any distributional assumptions on consumers' tastes for car attributes, we allow for correlation in tastes, and we do not need to make assumptions on the total market size and consumer choice sets.

By exploring the effects of consumer- and purchase-related factors on the valuation of fuel costs, our study also contributes to the literature investigating the role of consumer heterogeneity in the discounting of future energy costs (e.g., Hausman, 1979, Coller and Williams, 1999; Newell and Siikamäki, 2015). These studies have typically been based on stated preferences from choice experiments. Our research provides empirical evidence based on revealed preferences from actual transactions. We found that a better financial ability, a higher level of education, and brand loyalty facilitate a better understanding of the benefits of investments in fuel-efficient vehicles. Some of the heterogeneity determinants we investigate have not yet been studied in the literature on the consumer valuation of energy costs. In this vein, we also address the avenue for future research proposed by Grigolon et al. (2017) by studying the reasons for consumer heterogeneity in the valuation of usage costs. This understanding is important to assist policymakers in assessing policy instruments to deal with the externalities related to car use. Data on car choices at the individual level with provided consumer characteristics and expectations regarding car usage allow us to accomplish this aim.

The remainder of this paper proceeds as follows. In section 3.2 we present the conceptual framework and the methodology applied. Section 3.3 describes the data and provides initial insights for the following estimation, the results of which are presented in section 3.4. In section 3.5, we compare our findings on the determinants of consumers' valuation of future fuel costs to those in the previous literature and discuss the resulting policy implications. Section 3.6 concludes, highlights the conceptual contributions and limitations of the study, and proposes future research directions.

3.2 The Model

We use the hedonic discrete choice model (Bajari and Benkard, 2005) to recover individual valuations of future fuel costs and to investigate the effects of consumer- and transaction-related characteristics on the variation in this valuation. In the hedonic discrete choice model, a consumer (n) is assumed to purchase a product (j) that provides the highest utility for a bundle of its attributes subject to a consumer's budget. The budget is given by the consumer's income Y_n that is distributed among the purchase of a product and the consumption of all other goods (outside option). The utility function is assumed to have a known parametric functional form (Equation 3.1) for identification purposes (see also Bajari and Kahn, 2005).

$$U_{nj} = \beta_{n,PVFC}\text{PVFC}_{nj} + \sum_k \beta_{n,k} X_{kj} + \beta_{n,\xi}\xi_j + (Y_n - P_{nj}) \tag{3.1}$$

The utility depends on the present value of fuel costs (PVFC), other car characteristics observed (X_{kj}) and unobserved by the analyst (ξ_j), and the income (Y_n) net the paid price (P_{nj}). The coefficients $\beta_{n,PVFC}$, $\beta_{n,k}$, $\beta_{n,\xi}$ represent individual consumer tastes for the respective car characteristics, and $(Y_n - P_{nj})$ is a consumer's spending on the outside option. The price of the outside option is normalized to unity for identification purposes. The vehicle price is modeled by a hedonic price function, i.e., $P_{nj} = \mathbf{p}(X_{kj}, \xi_j)$, which defines how the price of a product varies with its underlying attributes and reflects a combination of implicit values for each attribute of a durable good (Rosen, 1974). From the first-order condition (FOC), the marginal rate of substitution between a product attribute k and the outside good equals to the partial derivative of the hedonic price function with regard to this attribute for the chosen product j^* (see Equation 3.2). The rate reflects the willingness-to-pay for marginal improvements in the attribute.

$$\frac{U_{nj}}{\partial X_{kj}} / \frac{\partial U_{nj}}{\partial (Y_n - P_{nj})} = \frac{\partial \mathbf{p}(X_{kj^*}, \xi_{j^*})}{\partial X_{kj}} \tag{3.2}$$

Our main focus is on the consumer valuation of the present-discounted value of expected fuel costs ($\beta_{n,PVFC}$). Formally, the value of PVFC depends on fuel prices (FP, €/liter), a vehicle's fuel consumption (FC, liter/100 km), the annual kilometers driven (KM), the length of car ownership (T, years), and the interest rate (r). We follow the previous literature and assume that consumers' expectations of future fuel prices follow a random walk for real fuel prices measured at the time of a car purchase (see e.g., Anderson et al., 2013). The interest rate is taken as exogenous and fixed at the level that corresponds to the average market interest rate (similar to Allcott and Wozny, 2014). We discuss the implications of this assumption below. We differ from previous studies in that we use information in our data on the stated expected driving intensity and car ownership length to construct individual PVFC values (Equation 3.3). The values that consumers place on the expected fuel expenses are then identified by comparing a variation in the individual PVFC values with that in the prices paid by buyers of identical car specifications. A highly detailed definition of car specifications allows us to mitigate the possible effect of omitted car attributes on the estimation (more details are given in Section 3).

$$PVFC_{nj} = \sum_{t=0}^{T_n} \frac{1}{(1+r)^t} \times (FP \times KM_n \times FC_j) \tag{3.3}$$

The utility specification in this setting is given in the "willingness-to-pay" space (see e.g., Train and Weeks, 2005). Hence, the individual's willingness-to-pay for marginal savings in PVFC is given by $\beta_{n,PVFC}$ after controlling for tastes for other product attributes, i.e. $\frac{\partial U_{nj}}{\partial PVFC_{nj}} / \frac{\partial U_{nj}}{\partial (Y_n - P_{nj})} = \beta_{n,PVFC}$. For a rational (cost-minimizing) consumer, $\beta_{n,PVFC}$ should equal -1. If $|\beta_{n,PVFC}|$ is less (more) than one, then consumers undervalue (overvalue) potential fuel savings. The parameter $\beta_{n,PVFC}$ is also referred to as "attention weight", "future valuation", or "valuation weight" in the literature (e.g., Allcott and Greenstone, 2012; Allcott and Wozny, 2014). Also note that the recovered valuation parameter is isomorphic to both the implicit discount rate at which consumers discount future costs and the consumers' required payback period. On one hand, a valuation weight for future fuel savings lower than one also implies a discount rate higher than the (assumed) market rate and a shorter required payback period. On the other hand, if we assume a higher interest rate (r) or a shorter ownership period (T) in our computation of PVFC, we will obtain a higher valuation parameter.

In our analysis, we first recover individual implicit values for PVFC along with other car attributes by estimating the hedonic price function nonparametrically. The nonparametric estimation uses the portion of data around the chosen bundles of product attributes, individual PVFC values, and purchase prices. We assume that locally the hedonic price function takes the semi-logarithmic functional form of dependency (Equation 3.4).

$$\ln P_{nj} = \mathbf{p}(PVFC_{nj}, X_{kj}, \xi_{nj}) \tag{3.4}$$

The local semi-logarithmic specification fits the data best and is in line with the majority of previous studies on hedonic price regression (e.g., Triplett, 1969; Matas and Raymond, 2009). By estimating Equation 3.4, we test whether the individually paid prices for vehicles move one-for-one with changes in the individual values for PVFC after controlling for other product attributes. The residuals of the hedonic price regression reflect the unobserved product attribute, ξ_j, which is assumed to be one-dimensional and mean-independent of the observed product attributes. Based on the utility and hedonic price specifications, individual willingness-to-pay values for savings in future fuel costs are computed as in Equation 3.5, where $\frac{\partial \widehat{\mathbf{p}}(\cdot)}{\partial PVFC}$ is the estimate of the price gradient with respect to PVFC.

$$\widehat{\beta}_{n,PVFC} = \frac{\partial \widehat{\mathbf{p}}(\cdot)}{\partial PVFC} \tag{3.5}$$

In the next step, we explore the joint distribution of the estimated individual valuation of fuel costs and heterogeneity determinants. The modeled relationship is presented in Equation 3.6, where Z_n contains heterogeneity characteristics of interest and η_n is an idiosyncratic preference shock at the individual level that is assumed to be exogenous and independent of other consumer-specific covariates, $E(\eta_n|Z_n) = 0$.

$$\widehat{\beta}_{n,PVFC} = h(Z_n) + \eta_n \tag{3.6}$$

3.3 Data and Descriptive Evidence

3.3.1 Data sources and sample

For our analysis, we use a dataset that contains information on a sample of new vehicle models purchased in Germany over a period of seven years – from 2000 to 2006 (henceforth, transaction data). The data are collected by a German market research company through an anonymous survey of consumers who bought a new car within the previous three months (see Appendix 3.7 for more details). The transaction data include the date of consumers' car purchase, the attributes of and prices paid for the chosen cars, and various consumer- and purchase-related characteristics for each respondent. Consumers stated values for their anticipated annual car use and their length of ownership of a previously owned car. We use these values to construct individual PVFC values for our analysis.

In the transaction data, the purchased vehicles are described by the car model name (e.g., VW Golf), the engine type (e.g., diesel), the transmission (e.g., manual), the horsepower (e.g., 125 HP), and displacement (e.g., 1997 cm^3) for each month-of-year observation. We additionally retrieve values for the fuel consumption (the weighted average between city and highway values), weight, and car class of the purchased vehicles from a web database of the largest automobile club in Germany, ADAC (http://www.adac.de/infotestrat/autodatenbank). ADAC provides detailed information on the attributes of all unique car specifications available in Germany since the mid-1990s. We merge the additional information from ADAC to the transaction data for each observation. The month-of-year of the purchases serves as an additional condition for identifying a precise car match based on the dates of the production start and end given in the ADAC database. Information on fuel prices at the monthly level for 2000-2006 also comes from the ADAC web database. As an interest rate to discount future fuel costs, we take 3%, which is an average of the ECB interest rates for the main refinancing operations over 2000-2006 provided by the German Federal Bank (http://www.bundesbank.de/). Table 3.1 gives an overview of the fuel prices and interest rates over time. All monetary values in the data are inflation-adjusted by using the consumer price index (CPI), which is normalized to one in April 2010.

Table 3.1: Fuel prices and benchmark interest rates over time

Year	Gasoline (2010 € cent/l)	Diesel (2010 € cent/l)	Interest rate, %
2000	118.33	93.33	4.04
2001	116.75	93.58	4.25
2002	118.06	94.37	3.21
2003	121.91	98.73	2.25
2004	124.52	103.02	2.00
2005	131.57	114.68	2.02
2006	136.35	118.08	2.79
Average	123.93	102.26	2.94

NOTE: The table gives an overview of the average annual fuel prices and interest rates from 2000 to 2006. Interest rate is the ECB rate for the main refinancing operations given by the German Federal Bank at http://www.bundesbank.de/. Information on fuel prices comes from the ADAC web database (http://www.adac.de/infotestrat/autodatenbank).

For the analysis, we use observations only on passenger cars with diesel or gasoline engines. Other types of cars are excluded because of their minimal representation among car purchases during the considered period ($< 2\%$). We also focus on consumers who purchased a car privately (in contrast to corporate purchases). For the analysis, we use observations with the price and PVFC values between the 1^{st} and the 99^{th} percentiles of their distributions within each car class and engine type. The final dataset contains 121313 observations. There are 38761 (31.95%) and 82552 (68.05%) observations for diesel and gasoline vehicles, respectively. We provide the detailed descriptive statistics for the attributes of the purchased cars in the Appendix (see Table 3.24).

3.3.2 Description of consumer heterogeneity

Buyers' differences can be described by socio-demographic and purchase-related characteristics, individual expectations of car utilization, and heterogeneous tastes for car attributes. In this study, we aim to understand how variation in consumers' valuation of the expected future fuel costs relates to the observed consumer- and transaction-specific characteristics.

First, we look at variations in both, the present values of fuel costs and individual prices paid by different consumers for the same car specifications. Additional information in our data on supplementary car features that the consumers individually selected at the time of a car purchase enables us to use very detailed product definitions. We distinguish the purchased vehicles by car class, engine type, model name, model year, transmission, horsepower, displacement, and a set of additional car features, including a sunroof, air conditioning, cruise control, leather seats, a GPS navigation system, and a park distance sensor. Accounting for these additional attributes is especially important for classes of larger cars, in which these features are more common (see Table 3.2).

Table 3.2: Mean shares of additional car features

	Minis	Superminis	Compact class	Middle class	Upper middle class	Upper class
Sunroof[a]	0.17	0.09	0.10	0.15	0.32	0.64
Automatic air conditioning[a]	0.04	0.17	0.30	0.38	0.41	0.44
Manual air conditioning[a]	0.26	0.35	0.21	0.07	0.06	0.03
Cruise control[a]	0.02	0.08	0.25	0.44	0.75	0.80
Leather seats[a]	0.03	0.03	0.07	0.17	0.42	0.58
GPS navigation system[a]	0.01	0.02	0.06	0.14	0.38	0.69
Park distance sensor[a]	0.02	0.07	0.17	0.30	0.47	0.55
Sum of extra features	0.55	0.82	1.15	1.65	2.80	3.73
N observations	4158	23958	48116	35160	9252	669

NOTE: The table presents the average choice shares and the total amount of supplementary features of each car class over engine types. (a) Presented by a dummy variable that equals one if the feature is present.

In our analysis, the present value of fuel costs varies at the individual level due to the observed consumer heterogeneity in anticipated vehicle usage and length of car possession. We use the length of previous car possession to approximate the car ownership length for the new vehicle. Later, we also discuss the robustness of our results to this assumption. Table 3.3 provides average values for the summary statistics (mean and standard deviation) of the purchase prices, PVFC, and its consumer-specific components within the same products. For example, values of the standard deviation for the purchase price show how consumers on average differ in the prices they paid for the same car qualities. A one-standard-deviation change in the transaction price varies from one to six thousand euros over both engine types, indicating vast heterogeneity in consumers' willingness-to-pay values. The dispersion in purchase prices increases for more expensive cars. This finding might indicate a high heterogeneity in luxury car buyers' traits, preferences, and bargaining power with car dealers.

Table 3.3: Heterogeneity in purchase prices, PVFC, and its consumer-specific components within the same products (average values)

		Minis	Superminis	Compact class	Middle class	Upper middle class	Upper class
				Diesel vehicles			
Purchase price (2010€)	Mean	16,338.69	19,154.53	26,197.62	33,749.17	45,528.92	66,851.66
	SD	1,216.76	1,433.24	1,969.30	2,489.53	3,415.14	5,280.34
PVFC (2010€)	Mean	3,422.64	3,883.72	4,718.48	5,602.40	6,737.98	8,148.74
	SD	1,915.30	2,073.53	2,210.69	2,556.37	3,143.57	3,946.22
Net PVFC (2010€)	Mean	2,668.13	3,005.18	3,713.32	4,373.93	5,345.53	5,901.87
	SD	1,353.01	1,672.65	1,883.14	2,090.10	2,601.47	3,158.42
Expected annual KM	Mean	15,235.41	17,841.35	18,136.32	18,745.54	19,060.83	19,641.95
	SD	5,037.52	5,386.54	5,509.92	5,656.25	6,341.62	8,470.17
Holding length, years	Mean	5.12	4.95	5.09	5.07	5.06	4.65
	SD	2.60	2.41	2.29	2.22	2.28	2.33
Number of products		42	792	2939	4108	1909	132
Number of consumers		234	4134	14884	14328	4869	312
				Gasoline vehicles			
Purchase price (2010€)	Mean	13,460.99	17,104.27	23,424.80	31,396.87	45,186.61	79,084.14
	SD	1,214.18	1,337.11	1,779.75	2,152.96	3,137.35	6,177.42
PVFC (2010€)	Mean	3,500.58	4,330.55	5,617.86	6,737.22	8,340.06	10,100.88
	SD	1,840.89	2,108.61	2,492.23	2,944.20	3,615.84	4,047.65
Net PVFC (2010€)	Mean	2,613.73	3,141.84	4,416.06	5,147.67	6,795.43	8,610.68
	SD	1,399.16	1,514.85	1,891.16	2,136.18	2,702.30	3,067.04
Expected annual KM	Mean	9,841.12	10,458.76	12,179.19	13,318.79	14,741.26	15,911.40
	SD	3,538.79	3,490.46	4,033.36	4,321.14	5,145.92	5,567.75
Holding length, years	Mean	5.73	6.02	5.78	5.47	5.35	5.06
	SD	2.80	2.54	2.36	2.29	2.20	1.95
Number of products		309	2204	4881	5459	1791	168
Number of consumers		3924	19824	33232	20832	4383	357

NOTE: The table reports average values of the summary statistics for the same product specifications. By first computing the values for the mean and standard deviation of the variables for each car specification, the averages of these values are then taken. A product specification is defined by the car model, engine type, transmission, horsepower, displacement, and a set of supplementary features (e.g., sunroof, leather seats, etc.). Net PVFC is computed as a present-discounted value of annual fuel costs that are left to bear after subtracting tax-deductible expenses for a potential amount of kilometers driven for business purposes. The number of consumers is the total number of observations (not product-specific) within the engine type and car class.

In line with our expectations, buyers of diesel vehicles anticipate driving more annually than those of gasoline vehicles. The length of car ownership is greater among gasoline car owners, without significant variations across car classes. The holding length values are comparable to the average values of official statistics for Germany (6 years; see www.statista.com). Due to lower values for both diesel (fuel) prices and fuel consumption, the discounted values of fuel costs (PVFC) for diesel vehicles are significantly lower than those for gasoline vehicles (despite a higher average driving intensity) for all but the mini car classes. Dispersion of these values is significant over all car classes for both engine types. This finding indicates that some consumers expect to incur €2000-€4000 more or less in fuel expenses compared to the mean values for the car class. For our analysis, we also adjust the values of expected annual fuel expenses for the possibility that a person can use the vehicle for business trips. In Germany, individuals may deduct the value of fuel costs for a work-related car usage from their annual income tax values. The net PVFC is computed as a present-discounted value of annual fuel costs that are left to bear after subtracting tax-deductible expenses for a potential amount of kilometers driven for business purposes. These values are considered to better reflect a relationship between the individual fuel costs and the individual willingness to invest upfront in a more fuel-efficient car. Details on the construction of the net PVFC are given in Appendix.

The descriptive statistics for consumer- and transaction-specific characteristics that are used in the later analysis to determine their roles in the degree of consumers' valuation of future fuel costs are given in Table 3.4 (see also Appendix for more details on the variables). To facilitate the following discussion, all determinants are grouped into three types – characteristics related to demographics, car usage, and capital constraints. We discuss the effects of the investigated determinants on the individual valuations of fuel costs when we present the empirical results in Subsection 3.4.3.

Table 3.4: Consumer- and purchase-related characteristics

		Diesel vehicles (N = 38761)		**Gasoline vehicles** (N = 82552)	
Characteristics	Units	Mean	SD	Mean	SD
Demographics					
Gender ("male" = 1)	0/1	0.83	0.38	0.72	0.45
Age	years old	48.22	13.56	52.15	14.57
Family size	number	2.64	1.10	2.39	0.98
Children under 18	number	0.52	0.87	0.35	0.71
University degree ("yes" = 1)	0/1	0.28	0.45	0.20	0.40
Town size	group	3.89	1.92	4.21	2.02
Region ("east" = 1, "west" = 0)	0/1	0.13	0.33	0.24	0.43
Capital constraints					
Monthly net income	group	8.43	2.76	7.39	2.88
Financing ("savings" =1)	0/1	0.60	0.49	0.64	0.48
Financing ("loan" =1)	0/1	0.35	0.48	0.32	0.47
Considered a used car ("yes"=1)	0/1	0.33	0.47	0.28	0.45
Car usage					
Holiday driving ("frequent usage"=1)	0/1	0.93	0.25	0.86	0.34
Weekend driving ("frequent usage"=1)	0/1	0.71	0.45	0.67	0.47
Cars in use	number	1.65	0.72	1.48	0.65
Two cars or more ("yes" = 1)	0/1	0.53	0.50	0.40	0.49
Same make as previous ("yes"=1)	0/1	0.53	0.50	0.58	0.49

NOTE: The table presents summary statistics (means and standard deviation) for the consumer- and transaction-specific characteristics used in the analysis. Averages for group variables (hometown size and income) are computed without the "not answered" option. Hometown size has 8 categories ranging from "$<$ 2,000" to "$\geq$ 500,000", with the median for both engine types being group 4 (20,000-49,999). Income has 15 categories ranging from "<€1,000" to "$\geq$€15,000", with the median for both engine types being group 8 ("€2,500-€2,999"). See Table 3.11 for more details.

3.4 Empirical Results

3.4.1 Hedonic price regression

We perform the entire investigation of the relationship between purchase prices and future fuel costs for buyers of identical passenger cars for six different car classes of two engine types (diesel and gasoline) separately. The main motivation for undertaking separate estimations is that the equilibrium conditions in each of these twelve markets (6 car classes $\times$ 2 engine types) can differ. First, technological differences between diesel and gasoline engines may result in different interdependencies between car prices and car characteristics. Second, consumers' preferences for car attributes and their attention to ongoing usage costs may structurally differ among engine types and car classes. Sallee (2014), for example, argued that consumers may correctly value fuel cost differences between vehicles of different classes but be unable or unwilling to determine these differences within a class. Additionally, we estimated the hedonic price regression by pooling over car classes while controlling for car class fixed effects. We did not find significant differences on average, but the valuation coefficients from the pooled regressions differ significantly from those for car classes in the separate regressions (see Table 3.23 for the robustness check estimates). Thus, we find it important to conduct estimations by car class to correctly investigate the extent of the valuation of future fuel expenses.

To recover individual tastes for PVFC (and other car attributes), we estimate the hedonic price regression using the local-linear nonparametric method described in Li and Racine (2004). Equation 3.7 presents a hedonic price specification, where α_ns are locally-estimated consumer-specific coefficients on the included car attributes.

$$
\begin{aligned}
\ln(\text{Price}_{njt}) = \mathbf{p}(&\text{PVFC}_{njt}, \text{HPW}_{jt}, \text{W}_{jt}, \text{Disp}_{jt}, \text{Automatic}_{jt}, \text{Extras}_{sjt}, \\
&\mu_j, \tau_t, q_t, r_n, \xi_{njt})
\end{aligned} \tag{3.7}
$$

Our primary interest is the estimate of the price gradient with respect to PVFC, $\dfrac{\partial \widehat{\mathbf{p}}}{\partial PVFC}$. The identified variation in the relationship between transaction car prices and PVFC comes from differences in these values among consumers and over time (net any seasonal variations controlled by year and quarter fixed effects) after controlling for preferences for other car attributes. Horsepower related to weight (HPW) and displacement ($Disp$) control for the car performance (e.g., Berry et al., 1995), and car weight (W) refers to the size of a car (e.g., Arguea et al., 1994). $Extras$ contains dummy variables that indicate whether the purchased car has any supplementary features of those presented in Table 3.2.

An extensive set of fixed effects is also added. To account for temporal changes in product qualities and the seasonality of purchases, fixed effects for year, τ_t, and quarter, q_t, for the purchase occasion are included. An indicator of whether the purchase is made in a west German or an east German state, r_n, is added to control for regional differences in prices (with prices in the east usually being lower) and other unobserved buyer and dealer characteristics that may vary by region. Additionally, fixed effects for make and model (e.g., Audi A3, BMW 1 Series, VW Golf, etc.), μ_j, control for unobservable car qualities, such as reliability, premium status, and other model-specific features that remain constant over time. In the estimation, the reference category is the first quarter of the year, the year 2000, the west region, a VW model (VW Lupo for minis, VW Polo for superminis, VW Golf for the compact class, VW Passat for the middle class, VW Touareg for the upper middle class, and VW Phaeton for the upper class), a displacement of "2000-2499" cm^3, and a manual transmission.

Because there are too many observations for most car classes to directly use a commonly applied cross-validation method in selecting smoothing parameters (the computational time necessary for the cross-validation methods is proportional to the squared number of observations), we apply an approach outlined in Racine (1993). The method is based on the fact that a window width for a variable k (h_k) is proportional to the variation in that variable (σ_k), the sample size (N), and the number of regressors (r), with a constant of proportionality c_k ("the scale factor") that is independent of the sample size, i.e., $h_k \sim c_k \sigma_k N^{-1/(2p+r)}$. Thus, one can conduct the bandwidth selection on a large number of subsets drawn randomly from the full dataset. By taking the median value over the scale factors from these subsets, one can proceed with estimation for the entire sample (for more details, see Hayfield and Racine, 2008). According to the rules discussed by Racine (1993), we estimate the local-linear hedonic price regression by using 50 resamples (without repetition), each with 230 observations, to select the smoothing parameters. The results are robust to the amount of resamples and the number of observations higher than 230. We use a Gaussian kernel for continuous variables and a Li-Racine kernel for discrete variables and apply the Li-Racine generalized product of kernel functions (Li and Racine, 2004; Hayfield and Racine, 2008).

Table 3.5 provides fit statistics for the estimated hedonic price regression. Overall, the results indicate a moderate to good fit of the hedonic regressions. We exclude observations for diesel vehicles from the smallest car class (minis) from our estimation because of too few observations (only 42 products; see Table 3.3). Summary statistics for the parameter estimates from the nonparametric hedonic price regression for all car attributes are presented in Table 3.6.

Table 3.5: Fit statistics for the nonparametric hedonic price regression

	Diesel vehicles					Gasoline vehicles				
Car Class	N used	MSE	MAPE	SE	R2	N used	MSE	MAPE	SE	R2
Minis						3924	0.0107	0.0087	0.0017	0.7078
Superminis	4134	0.0076	0.0069	0.0014	0.6648	19824	0.0103	0.0081	0.0007	0.6896
Compact class	14884	0.0067	0.0063	0.0007	0.7492	33232	0.0072	0.0066	0.0005	0.7749
Middle class	14328	0.0057	0.0057	0.0006	0.8184	20832	0.0054	0.0055	0.0005	0.8738
Upper middle class	4869	0.0055	0.0054	0.0011	0.8784	4383	0.0051	0.0051	0.0011	0.9279
Upper class	312	0.0077	0.0061	0.0050	0.9146	357	0.0088	0.0063	0.005	0.8666

NOTE: The table shows fit statistics for the local-linear hedonic price regression with a Gaussian kernel for continuous variables and a Li-Racine kernel for discrete variables. MSE is the mean square error; MAPE is the mean absolute percentage error; SE refers to standard errors; and R^2 is a pseudo-R^2.

3.4.2 Recovered consumer valuation of fuel costs

Individual valuation of fuel costs ($\widehat{\beta}_{n,PVFC}$) is given by the estimate of the price gradient with respect to PVFC that is evaluated at the prices consumer paid for the purchased vehicles. The cost-minimizing trade-off between PVFC and purchase price by a "rational" consumer requires that the willingness-to-pay for a €1 reduction in PVFC equal €1. Table 3.6 provides summary statistics for the estimates of this value. Here, the mean values along with the standard deviation, median, 10^{th} percentile, and 90^{th}-percentiles give an overview of the distribution of individual estimates. All price gradient values are statistically significant (not shown) and, as expected, are mainly negative (between 70% and 90% of the observations). The summary statistics are shown only for observations that have a negative price gradient of PVFC. A positive price gradient estimate implies that consumers have a greater preference for higher fuel costs, which is counter-intuitive. A higher number of positive price gradient estimates for larger car classes can be driven by both the variability common to nonparametric estimates and the presence of other factors that are not considered but important for luxury car buyers.

Overall, a high degree of undervaluation is evident. Only 0.26% of observations exhibit an overvaluation of fuel savings. On average, consumers' willingness-to-pay for a €1 reduction in future fuel costs is below €0.20. Buyers of diesel cars are characterized as having a lower degree of myopia on average than those of gasoline vehicles. Differences between the estimated willingness-to-pay for diesel and gasoline cars are statistically significant over all car classes. The valuation parameter that we recover in our analysis can also be used to determine individual implicit interest rates or payback periods. Our results suggest implicit interest rates of 109% and 144% over car classes on average for diesel and gasoline car owners respectively. The payback period for investments in fuel efficiency is less than one year on average. These values imply that consumers are very impatient in their decision-making and value savings in upfront costs more than savings in ongoing fuel expenses. As a robustness check, we also use different assumptions for the interest rate and the length of car ownership when computing the individual PVFC values (the results are in Table 3.23). A higher interest rate leads to a higher valuation weight on future fuel costs due to the interdependence of these two measures in describing consumer intertemporal preferences. As in previous studies, under a fixed time horizon (for example, 10 and 15 years), we find differences in the results in an expected direction, with a longer time period resulting in a lower valuation parameter. We also reestimate the hedonic price regression for only those consumers whose previous car was a new car. In our data, 67.86% of respondents previously possessed a newly bought car. On average, the length of ownership for

Table 3.6: Number and percentage of observations with negative price gradients of PVFC and summary statistics for the PVFC valuation parameter

	Diesel vehicles						Gasoline vehicles						Mean
	N (%)	Mean	SD	P10	Median	P90	N (%)	Mean	SD	P10	Median	P90	differences
Minis							3468 (88.56)	0.12	0.08	0.04	0.11	0.22	0.05 (p=0.003)
Superminis	3733 (90.37)	0.13	0.09	0.04	0.11	0.23	17247 (87.11)	0.09	0.08	0.02	0.08	0.16	0.04 (p<0.001)
Compact class	12207 (82.10)	0.14	0.11	0.03	0.12	0.25	27504 (82.88)	0.12	0.11	0.03	0.10	0.24	0.01 (p<0.001)
Middle class	11376 (79.55)	0.20	0.16	0.04	0.17	0.37	16384 (78.75)	0.16	0.16	0.03	0.12	0.33	0.04 (p<0.001)
Upper middle class	3825 (78.64)	0.23	0.19	0.05	0.19	0.47	3191 (72.90)	0.20	0.17	0.04	0.17	0.39	0.03 (p<0.001)
Upper class	226 (72.44)	0.45	0.55	0.03	0.31	1.05	297 (83.47)	0.41	0.35	0.11	0.32	0.90	0.04 (p=0.041)
Over car classes	31481 (81.33)	0.17	0.15	0.04	0.14	0.33	68091 (82.60)	0.13	0.13	0.03	0.10	0.26	0.04 (p<0.001)

NOTE: The table displays summary statistics for the valuation parameter $\beta_{n,PVFC}$ for a subset of observations with negative estimates for the price gradients of PVFC (82% of observations in total). The valuation parameter is evaluated by Equation 3.5 at the prices paid by consumers. N(%) is the number and percentage of observations (compared to the full sample) with a negative price gradient of PVFC. Mean differences are the differences in the average valuation parameters for diesel versus gasoline vehicles. The price gradient is estimated by a local-linear hedonic price regression with a Gaussian kernel for continuous variables and a Li-Racine kernel for discrete variables. All price gradient values are statistically significant.

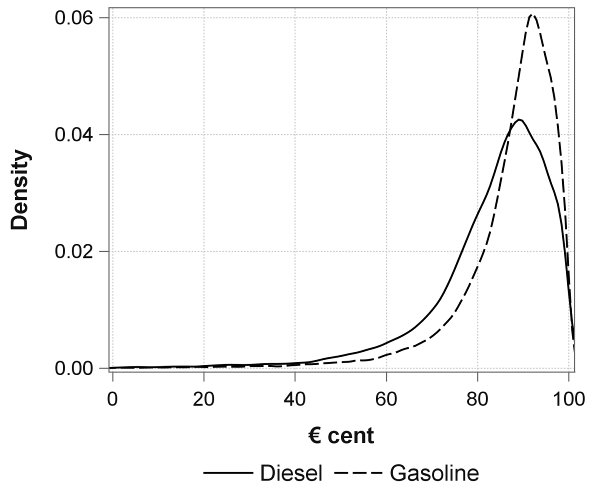
a previously owned car is approximately 6 months longer if it was bought new (see Table 3.19). However, we did not find statistically significant differences in the estimation results for the valuation parameters from those of our base model. Relatively high standard deviation values for the valuation parameter reflect high heterogeneity among consumers. In the next section, we aim at investigating how various factors can help to explain this heterogeneous degree of fuel cost undervaluation.

3.4.3 Determinants of the undervaluation of fuel costs

We regress the derived individual willingness-to-pay values for a reduction in the discounted future fuel costs on the consumer- and purchase-related characteristics to understand these values' role in consumers' valuations of energy-saving technology. A subsequent analysis is performed for the sub-sample with the negative price gradient estimates with respect to PVFC (82% of observations). For ease of interpretation, we construct a variable that indicates the extent of undervaluation of fuel savings and use it as our dependent variable. The variable is defined as 1 (€) less the derived individual valuation parameter ($\beta_{n,PVFC}$). Figure 3.1 shows that the distribution of the constructed dependent variable is negatively skewed. To obtain a comprehensive understanding of the effects for the selected heterogeneity determinants at different points along the conditional distribution of undervaluation, we apply quantile regression. In contrast to the conventional least squares regression, quantile regression estimates all conditional quantile functions (not only the mean function) of the response variable and is insensitive to extreme values in its conditional distribution (Koenker and Hallock, 2001). Quantile regression is also robust to distributional assumptions regarding the error terms.

A specification of the quantile regression in Equation 3.8 is estimated for each quantile τ of the conditional undervaluation distribution given all covariates, where $\gamma_0(\tau)$ and $\gamma_d(\tau)$ are the intercept and the corresponding estimate for each covariate in Z_d, respectively. The error term $\eta_n(\tau)$ is interpreted as an individual-specific taste shock. Heterogeneity determinants (Z_d) include gender, age, the number of children under 18, an indicator for university degree, hometown size, net monthly income, an indicator for considering the purchase of a used car, the financing method (savings versus loans), indicators for frequent holiday and weekend driving, the number of cars in use, and an indicator for purchasing the same car make as purchased previously. For the estimation we use the Frisch-Newton interior point method with standard errors obtained via the Markov chain marginal bootstrap

Figure 3.1: Distribution of consumers' undervaluation of future fuel costs



NOTE: The figure presents the kernel density function of the undervaluation distribution for both diesel and gasoline vehicles. Undervaluation is computed as 1 - (individual) willingness-to-pay for a €1 reduction in the discounted future fuel costs. The values are given in € cents.

(MCMB). It is recommended as a robust and computationally tractable estimation procedure for large datasets (Portnoy et al., 1997).

$$\text{Undervaluation}_n = \gamma_0(\tau) + \sum_d \gamma_d(\tau) Z_{dn} + \eta_n(\tau) \tag{3.8}$$

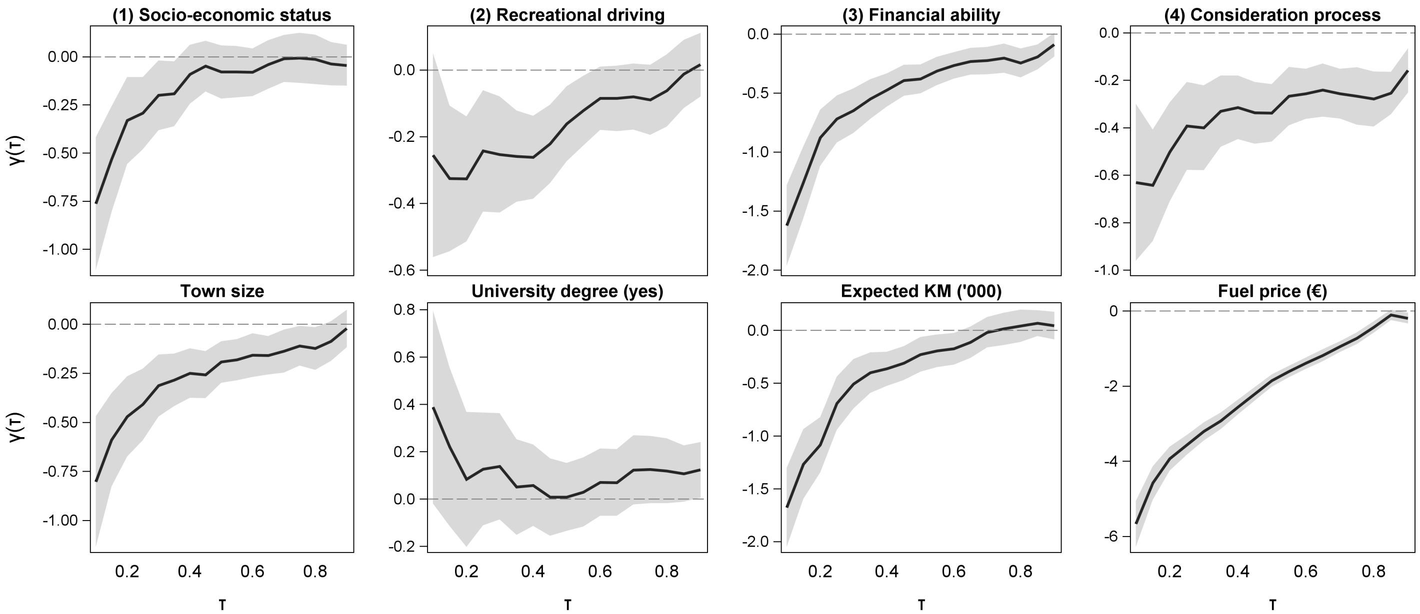
We estimate the quantile regression by including fixed effects for engine types and car classes. For the estimation, we replace missing values in the categorical variables with "NA" and treat this value as a separate category. The detailed results for all determinants can be found in Appendix (Table 3.21). Along with values for the covariate effects on the conditional undervaluation distribution, we report the ordinary least-squares (OLS) estimates. In our investigation, the conditional mean (OLS) estimates tend to under- or over-estimate the effects of the covariates. To assess the relative importance of each variable in explaining the undervaluation distribution, we standardize all variables prior to the estimation by subtracting their means and dividing by two standard deviations. This type of standardization allows the coefficients on continuous variables to be comparable with those on binary ones, as by construction, the latter have a standard deviation of one-half (in the case of equal probabilities). Thus, each coefficient $\gamma_d(\tau)$ shows a change in the conditional quantile of the undervaluation (in € cents) when the explanatory variable increases by two standard deviations, ceteris paribus.

Because many determinants are interrelated and may thus refer to the same underlying component, we also arrange all heterogeneity determinants into homogeneous clusters. For this purpose, we apply an oblique principal component cluster analysis (e.g., Rey et al., 2012; Enki et al., 2013), which groups together variables that are strongly related to one another and yet allows the clusters to be correlated. We should note that score values for clusters of variables are not always unequivocally interpretable, as the same score value can result from different combinations of the weighted variables. In our analyses, the resulting four clusters of variables have a relatively clear interpretation and yield results that are in line with the effects from a regression with non-clustered variables. The retained clusters have low-to-moderate inter-cluster correlations between 0.06 and 0.24 in absolute values. We include all details on the clustering procedure in Appendix.

The effects of the clustered and standardized determinants are presented in Figure 3.2 (see also Table 3.22), which depicts the changes in the coefficients over quantiles of the undervaluation distribution. Negative $\gamma_d(\tau)$ values for the effects indicate a lower myopia in terms of the expected future fuel costs. Overall, the estimated effects are found to be more pronounced at lower and average quantiles of the undervaluation distribution. The values for the standardized coefficients indicate that determinants that reflect capital constraints and consumers' financial ability make a greater contribution to the explanation of the valuation of future fuel expenses than other types of variables (such as the purposes of car use and the characteristics of the decision process). Expected annual driving and fuel prices both have significant negative effects on the degree of undervaluation. If a consumer expects to drive a lot or expects higher fuel prices, then the extent of myopia in the purchase decision decreases.

The effects of socio-demographic characteristics indicate that male and older drivers, and those with more minors in the family can better assess the potential savings in future fuel costs. This phenomenon can be linked to a reduced uncertainty in one's own driving preferences due to these consumers' longer experience with cars, their better assessment of car information, and the importance of any marginal changes in expenditures for consumers with larger families. For example, De Borger et al. (2016) found that an increase in the number of children in the household raises the demand for driving. Additionally, due to the lower disposable wealth for these consumers, the importance of making the "right" car choice should increase. These effects are summarized in the first cluster of variables as **"socio-economic status"**. Higher score values for this cluster correspond to being male, older, and having more children drivers. This cluster also includes a variable that indicates the financing method for the car purchase (own savings versus loans), with higher scores being linked to the use of savings. Educational level does not yield a significant

Figure 3.2: Effects of determinants on undervaluation of future fuel costs



NOTE: The figure depicts the quantile processes for each covariate based on the quantile regression. Explanatory variables are standardized to have means of zero and standard deviations of 0.5. Each coefficient shows a change in the undervaluation (in € cents) as the explanatory variable increases by two standard deviations. Negative $\gamma_d(\tau)$ values correspond to lower myopia. The number of observations used is 98873.

effect in the model with clustered variables. However, in the model that includes all determinants separately, holding a university degree results in lower myopia as well. The significant negative effect of hometown size shows that buyers from larger cities have lower myopia regarding fuel expenditures. This pattern may be explained by relatively lower income levels or a worse availability of various car specifications in smaller towns.

Previous studies have demonstrated that low-income households consistently place lower values on future fuel costs (e.g., Berkovec and Rust, 1985). In our study, we confirm this pattern. The cluster of variables that we label **"financial ability"** has higher values for buyers with higher incomes and for those who have more than one car in regular use. A better assessment of fuel costs for these consumers is explained by these consumers' better ability to invest in improved car quality and their greater experience with cars.

While some previous studies have shown that the purpose of car use significantly affects the choice of car type (e.g., Steg, 2005; Baltas and Saridakis, 2013), no studies have explicitly explored the role of this factor in consumers' valuation of fuel costs. Our results demonstrate that a higher expected car use for recreational purposes (holiday and weekend driving) improves consumers' recognition of the value of fuel economy, resulting in less bias. The combined effect of the holiday and weekend driving variables is given by the cluster component **"recreational driving"**.

Our last cluster of variables includes indicators for whether a consumer has considered purchasing a used car and whether the make of a previously owned car was purchased again. We refer to this cluster as the **"consideration process"**. Consumers with higher scores for this cluster are those who have considered purchasing new cars and those who have purchased the same car make. We link the negative effect of this group of variables on undervaluation to the complexity of the decision process. A smaller bias for brand-loyal consumers may be explained by the costs of processing and searching for additional information. By sticking to a previously purchased car make, consumers may reduce the choice complexity by evaluating car characteristics, including fuel costs, only for the preselected brand. Information on product attributes may also be more easily available and more reliable for new rather than used cars. Thus, the results for these variables provide support for the theory of choice overload (e.g., Iyengar and Lepper, 2000) and are in line with the findings of studies on consumers' strategies to deal with information overload (e.g., Walsh et al., 2007; Foxman et al., 1992). Consumers' consideration of a used car can also be motivated from an economic perspective. If a consumer has restricted financial resources, the second-hand market becomes a valid alternative to search for a vehicle (e.g., Guiot and Roux, 2010). In our sample, consumers with the lowest incomes tend to consider used vehicles more often (on average 1.5 times more often). Thus, being indicative of consumer financial ability, both variables – income and the consideration of used cars – have an impact on the valuation of fuel savings in the same direction.

3.5 Policy Implications

Our findings of a low valuation weight of future fuel costs and high implicit interest rates for buyers of new vehicles in Germany suggest that consumers value savings in upfront costs much more than savings in ongoing fuel expenses. In this case, consumers do not choose cost-effective, energy-efficient technology despite its lower fuel costs at current energy prices – a pattern defined in the literature as the "energy-efficiency paradox" (Jaffe and Stavins, 1994). Many studies discuss potential explanations for this phenomenon (e.g., Allcott, 2011; Gillingham and Palmer, 2014; Gerarden et al., 2015; Metcalf and Hassett, 1999; and Tietenberg, 2009, to name a few). All factors have been related either to market failures (insufficient information provision and capital constraints) or behavioral anomalies (inconsistent time preferences, cognitive limitations, choice inertia, and usage uncertainty). The recommendations for policy implementations depend on the prevailing explanations. A Pigouvian tax on energy that optimally deals with energy use externalities under the full valuation of energy costs would not provide the first-best outcome if agents are imperfectly informed or exhibit behavioral anomalies (e.g., Allcott and Greenstone, 2012).

In our investigation, we find that socio-economic conditions explain many differences among consumers in terms of their degree of fuel cost valuation. Factors that relate to car buyers' financial ability and the importance of capital constraints make a significant contribution to reducing consumers' myopia. Consumers with a lower level of financial stability may not be able to afford cars with better fuel economy and therefore must make suboptimal choices. Because investment inefficiencies in consumers' decisions may discourage manufacturers from developing cars with better fuel economy, it is also crucial to provide economic incentives on the supply side. Proper functioning of the capital market and the provision of subsidies to consumers and/or manufacturers are thus important to lower the financial burden in the diffusion and adoption of fuel-efficient vehicles.

The recovered consumers' undervaluation of fuel savings from cars with better fuel economy might be caused by either consumers' limited attention to fuel expenses or insufficient information to identify economically optimal choices. Insufficient information refers to a market failure, whereas limited attention refers to a behavioral failure. The latter is also linked to nonstandard decision-making directly or nonstandard beliefs indirectly through consumers' cognitive limitations (Gillingham and Palmer, 2014; DellaVigna, 2009). It is difficult to disentangle these causes empirically. However, several insights can be inferred from the present research. For our data, information on car fuel efficiency during the sample period (2000-2006) may have been costly for consumers to obtain. The national German regulation regarding energy efficiency labeling for new passenger cars came into force only after November 2004. Although a re-estimation of the hedonic price regression for the 2005-2006 period does not yield significantly different valuation parameters (see Table 3.23), data on recent years may indeed lead to a higher valuation parameter, as information provision has improved over time. However, for example, in their recent study on the U.S. automobile market, Allcott and Knittel (2017) found no statistically significant effect of information on the average fuel economy of purchased vehicles.

In addition to the costs of acquiring information, limited attention to energy cost savings can also result from cognitive limitations and the difficulty of processing all information correctly. One of the errors that consumers can make in their perceptions of total energy costs is presented by the "MPG Illusion" (Larrick and Soll, 2008; Allcott, 2011), which suggests a systematic misperception of improvements in fuel efficiency when expressed in miles per gallon (MPG). Although this perceptual error does not indicate the undervaluation of fuel cost savings per se, it highlights computational difficulties that consumers may encounter. Because in Germany, cars' fuel economy is presented in liters per kilometer, a measure linearly linked to fuel costs, it should have been easy for consumers to assess potential fuel savings from more fuel-efficient vehicles. Therefore, the recovered undervaluation of energy cost savings in our study is explained by other market and behavioral failures.

Because we observe only one point of consumers' investment decisions, we cannot interpret the high implicit discount rate (or high degree of myopia) as being a result of time-inconsistent preferences. For this, one must observe discount rates of the same consumers over time. However, a lack of self-control (Thaler and Shefrin, 1981), which is also related to the time-inconsistency of preferences, may still be an explanation for our findings. A less-fuel-efficient vehicle with a lower purchase price may appear "tempting" to consumers despite its relatively high operating costs. Thus, as Tsvetanov and Segerson (2013) proposed, energy efficiency standards that limit the supply of cheap but fuel-inefficient vehicles could serve as a commitment device to address investment inefficiencies in consumer choices.

The role of uncertainty in consumers' expectations regarding car usage should have a lower impact on the results of our investigation than on those of previous studies because the sample of consumers used in the current analysis consists of those who had previously possessed a car. Experience with a car should help consumers understand their own driving preferences. Additionally, we control for the purpose of car use as an indicator of differences in driving preferences. The results indicate that if consumers expect to use a car relatively frequently for weekend or holiday trips, their willingness to pay for a reduction in fuel costs increases.

The recovered consumer heterogeneity in the degree of investment inefficiency also highlights the importance of designing targeted policies to motivate consumers' choices toward cars with better fuel economy (as also proposed in, e.g., Allcott et al., 2015 and Allcott et al., 2014). As Allcott and Greenstone (2012) indicated, "welfare gains will be larger from a policy that preferentially affects the decisions of consumers subject to investment inefficiencies" (p.5). Our results suggest that capital constraints and the potential complexity of car choice tasks are important determinants of the recovered undervaluation of car fuel efficiency. A set of complementary policies could help to reduce the energy-efficiency gap. In conjecture with information provision policies that contribute to a better understanding of potential savings in future fuel costs, financial incentive schemes could efficiently support consumers with tighter capital constraints. In addition to tools that address market failures, the development of social preferences could help to overcome certain behavioral failures. For example, consumer attention could be shifted to fuel efficiency as a signal of pro-environmental behavior to peers (Gsottbauer and van den Bergh, 2011). Hence, policy tools should aim at developing intrinsic (inner motivation) and extrinsic (external financial and non-financial) incentives for consumers to embrace better fuel efficiency.

3.6 Conclusion

Using observed choices of new cars by a sample of consumers in Germany within the 2000-2006 period, the present study first quantified the direction and magnitude of these consumers' trade-off between the higher upfront capital costs and the lower ongoing usage costs of a more fuel-efficient car at the time of a car purchase. Second, this study explained the recovered heterogeneity in consumers' valuation with the help of observed consumer- and purchase-related characteristics.

During our analysis, we controlled for various dimensions of consumer heterogeneity. Along with heterogeneity in tastes for car attributes, we accounted for consumer differences in the expected car usage intensity and car ownership length. These additional sources of consumer heterogeneity allowed us to contrast the variation in the individual values for present-discounted fuel expenses with that in the prices individually paid by buyers of identical cars. This process constituted our identification strategy to recover consumers' valuation of potential fuel savings from better fuel economy. A detailed definition of car specifications enabled the analysis to control for many car attributes (including supplementary features such as leather seats or a sunroof), thus reducing a potential source of omitted variable bias.

We recovered individual values for the present-discounted fuel costs in a non-restrictive way by estimating a nonparametric price regression within the hedonic discrete choice model. The applied framework does not require distributional assumptions on consumer tastes for car attributes. It uses a variation in the observed choices among bundles of car attributes and individual PVFC and relates this variation to that in prices. The nonparametric estimation also accounts for correlation in consumer tastes for car attributes without needing to model the variance-covariance matrix.

In our study, we found that consumers do not fully recognize the value of cost-effective, energy-efficient technology at the time of purchasing a car. The results remain robust to various assumptions on the interest rate, the length of ownership, and the time period under investigation. The rate at which consumers undervalue future energy costs varies significantly across buyers of various engine technologies and car classes. We also explored the effects of various determinants on the extent of consumers' valuation of future fuel savings from a more fuel-efficient car. Some of these factors have not yet been discussed in the literature on consumers' valuation of energy costs (e.g., considering the purchase of a used car and recreational driving). Using quantile regression, we recovered the covariate effects for various quantiles of the conditional distribution for the valuation parameter.

There are several possible concerns and extensions of the present analysis. First, the current paper did not account for potential rebound effects of reduced fuel costs, either direct (impact on car usage) or indirect (impact on the consumption of other energy-consuming goods). We assumed that annual kilometers driven remain constant over the entire car ownership period and are equal to the consumers' stated expected driving intensity. We found this assumption justifiable for the present research because we aimed at recovering the value of fuel costs for consumers at the time of car purchase conditional on their expected driving. Additionally, in our application, we do not consider a PVFC measurement error. If PVFC is measured with error, the recovered undervaluation may partially be a result of attenuation bias rather than a bias in the consumer decision-making. However, the noise-to-signal ratio should be unrealistically large (around six) to be the only reason for the low valuation weight we obtain. Furthermore, the results of our second-stage analysis of the effects of heterogeneity determinants on the valuation distribution should not be affected by the PVFC measurement error.

Depending on the available data, future research could apply the framework used in this study to other energy-using durable goods and explore other determinants of consumer heterogeneity in the valuation of future energy costs. Additionally, information on the characteristics of other cars within multi-vehicle households could enable researchers to test whether differences in the valuation of fuel savings depend on a household's household car portfolio. With data for longer and more recent time periods, the effects of current environmental policies on consumer preferences could also provide new insights.

3.7 Appendix

3.7.A Survey details

The dataset used in the study is provided by a market research company for (non-commercial) scientific research. A sample of new car buyers in Germany was surveyed briefly after the purchase (within the first 3 months). The survey was conducted by phone (CATI). We do not have information on the response rate. The dataset contains information on the car models purchased by a sample of consumers along with the car attributes, prices paid for the chosen cars, and various consumer- and purchase-related characteristics. We use a sample of private buyers of cars with gasoline or diesel engines from six car classes over a time period of 7 years (see Table 3.7).

The sample of respondents we use in our analysis is comparable to new car buyers and the population, with only slight differences in certain characteristics (e.g., there are only repeat car buyers in the sample; Table 3.9). The sources of information for new car buyers and the population are given in Table 3.10. The representation of car classes in the survey is also similar to those shares in new car registrations in Germany (Table 3.8).

Table 3.7: Description of the data sample for investigation

	Conditions
Time period	monthly level, 2000-2006
Engine type	Gasoline; Diesel
Car classes	Minis; Superminis; Compact; Middle; Upper middle; Upper
Purchase price	$\in [1; 99]$ percentiles for each car class
PVFC	$\in [1; 99]$ percentiles for each car class
Car ownership	Private

Table 3.8: Car class shares in the survey sample and new car registrations in Germany (average values for 2000-2006)

Car class	Sales shares, %	Survey shares, %
Minis	4.94	3.43
Superminis	21.02	19.75
Compact class	36.86	39.66
Middle class	28.20	28.98
Upper middle class	7.89	7.63
Upper class	1.08	0.55
Number of observations	3.33×10^6	121313

NOTE: Average car class shares in new car registrations are based on information at www.kba.de.

Table 3.9: Characteristics of the data sample compared to the population and new car buyers in Germany (average values for 2000-2006)

			Survey	Population	New car buyers
Number of persons			121313	82.54×10^6	3.33×10^6
Gender	(Male=1; Female=0)		0.75	0.49	0.71
Age	(number)		50.89	41.81	49.27
Net monthly income	(€)		2500-2999[a]	1467.43	2910.71
	Not answered	(%)	12.99	NA	5.00
	Under €1000	(%)	1.06	NA	1.80
	€1000 - €1249	(%)	2.48	NA	3.00
	€1250 - €1499	(%)	4.39	NA	6.40
	€1500 - €1749	(%)	5.91	NA	7.40
	€1750 - €1999	(%)	7.26	NA	8.40
	€2000 - €2499	(%)	16.91	NA	16.20
	€2500 - €2999	(%)	10.40	NA	15.20
	€3000 - €3499	(%)	12.08	NA	12.40
	€3500 - €3999	(%)	11.63	NA	7.80
	€4000 and more	(%)	14.89	NA	16.40
Number of kids under 18	(number)		0.40	0.38	NA
Family size	(number)		2.47	2.11	NA
Region	(East=1; West=0)		0.20	0.16	NA
Two and more cars in use	(share)		0.44	0.34	NA
First acquirers	(share)		0	0.22	0.13
Repeating car buyers[b]	(share)		1	0.78	0.87
Previous car was new	(share)		0.68	NA	0.64
Annual distance driven (Diesel)	(kilometers)		18555	19389	NA
Annual distance driven (Gasoline)	(kilometers)		12199	11537	NA
Diesel cars in new registrations	(%)		31.95	39.12	
Gasoline cars in new registrations	(%)		68.05	60.63	

NOTE: "NA" stands for "not available". (a) The average income of the sample corresponds to group 8 (the precise average is 7.72). (b) The share for repeat car buyers includes both buyers of an additional car and buyers of a car as a replacement for the previous one.

Table 3.10: Sources of data for the population and new car buyers (2000-2006)

		Source
Number of HH	Population	https://de.statista.com/statistik/daten/studie/156950
	New car buyers	https://www.statista.com/statistics/587730
Gender	Population	https://www.destatis.de/DE/Publikationen/WirtschaftStatistik/Bevoelkerung/Bevoelkentwicklung2006.pdf
	New car buyers	https://de.statista.com/statistik/daten/studie/385492
Age	Population	https://www.destatis.de/DE/Publikationen/WirtschaftStatistik/Bevoelkerung/Bevoelkentwicklung2006.pdf
	New car buyers	https://de.statista.com/statistik/daten/studie/215576
Net monthly income	Population	https://de.statista.com/statistik/daten/studie/370558
	New car buyers	DAT-Reports 2001-2007 (https://www.dat.de/angebote/verlagsprodukte/dat-report.html)
Number of kids under 18	Population	https://de.statista.com/statistik/daten/studie/197783
	New car buyers	NA
Family size	Population	Federal Institute for Population Research (http://www.bib-demografie.de)
	New car buyers	NA
Region	Population	http://www.vgrdl.de/VGRdL/tbls/tab.jsp?rev=RV2014&tbl=tab20&lang=de-DE
	New car buyers	NA
Cars in use	Population	DAT-Reports 2001-2007
	New car buyers	NA
First acquirers/ Repeating car buyers	Population	DAT-Reports 2001-2007
	New car buyers	DAT-Reports 2001-2007
Previous car was new	Population	NA
	New car buyers	DAT-Reports 2001-2007
Annual distance driven	Population	https://www.diw.de/documents/publikationen/73/diw_01.c.433448.de/13-50-3.pdf
	New car buyers	NA
New car registrations by fuel type	Population	www.kba.de
	New car buyers	www.kba.de

3.7.B Construction of the key variables

Net PVFC

For our analysis, we additionally adjust the values of expected annual fuel expenses by accounting for the possibility that a person can use a vehicle for business trips. Individuals may deduct the value of fuel costs for work-related car usage from their annual income tax values. According to §9 of the Income Tax Act (Einkommensteuergesetz), the German government sets a fixed deduction rate per kilometer driven for business purposes at €0.30. This value is assumed to reflect all fuel expenses and maintenance costs related to a car's use per kilometer. In the current analysis, the limit for a distance after which the incurred fuel costs can be tax-deducted is set at a level equal to the median of expected annual driving within the car class for each engine type. For diesel car owners, this level varies between 18,000 and 20,000 km, whereas for gasoline car buyers, it varies between 10,000 and 15,000 km. The amount of kilometers driven above the set limits is multiplied by €0.15 (half of €0.30 to account for two-way trips in most cases) and is subtracted from the annual fuel expenses. The resulting net values for PVFC (net PVFC) are used in the following estimation. This variable is considered to better reflect a relationship between the individual fuel costs and the individual willingness to invest upfront in a more fuel-efficient car.

Heterogeneity determinants

Table 3.11 provides the number of observations for each group of the categorical consumer- and purchase-related characteristics. For the analysis, answer options for the variables that characterize how frequently a consumer expects to use a car for weekend and/or holiday trips have been grouped into two categories "frequent" and "infrequent" usage using the median-split methodology (Iacobucci et al., 2015). A variable for frequent car use for holiday trips equals one if the usage frequency was stated at the levels of "at least once a year" or more frequently (82.51% of the sample); a variable for frequent car use for weekend driving is unity if the usage frequency was stated as "at least once a month" or more frequently (60.89% of the sample).

Clustering of variables

To uncover the underlying structure of the determinants, we apply oblique principal component cluster analysis. Associated with each cluster is a linear combination of the variables in the cluster. We use the first principal component as a weighted average of the variables that explains as much variance as possible. The procedure begins with a single cluster and recursively divides existing clusters into two sub-

Table 3.11: Consumer- and purchase-related characteristics (group variables)

		N	Percent			N	Percent
	Hometown size				**Net monthly income, €**		
0	Not answered	547	0.45	0	Not answered	15764	12.99
1	< 2,000	10142	8.36	1	< €1000	1284	1.06
2	2,000 - 4,999	13117	10.81	2	€1000 - €1249	3012	2.48
3	5,000 - 19,999	32436	26.74	3	€1250 - €1499	5321	4.39
4	20,000 - 49,999	22881	18.86	4	€1500 - €1749	7166	5.91
5	50,000 - 99,999	11341	9.35	5	€1750 - €1999	8806	7.26
6	100,000 - 299,999	13987	11.53	6	€2000 - €2249	10152	8.37
7	300,000 - 499,999	4286	3.53	7	€2250 - €2499	10358	8.54
8	≥500,000	12576	10.37	8	€2500 - €2999	12618	10.40
	Overall	121313	100	9	€3000 - €3499	14654	12.08
				10	€3500 - €3999	14107	11.63
	Children under 18			11	€4000 - €4999	10091	7.90
				12	€5000 - €7499	6478	5.07
1	None	90211	74.36	13	€7500 - €9999	1411	1.16
2	One	16228	13.38	14	€10000 - €14999	662	0.55
3	≥Two	14874	12.26	15	≥€15000	557	0.46
	Overall	121313	100		Overall	121313	100
	Financing				**Number of cars in use**		
0	Not answered	5628	4.64	1	One	67569	55.70
1	Savings	75652	62.36	2	Two	44310	36.53
2	Loan	39869	32.86	3	Three	7679	6.33
3	Lease	164	0.14	4	≥Four	1755	1.45
	Overall	121313	100		Overall	121313	100

Table 3.12: Consumer- and purchase-related characteristics (cont'd)

	Initial response	Recoded response	N	Percent
		Weekend driving		
0	Not answered	NA	13843	11.41
1	Almost Every Day	Frequent	15245	12.57
2	At Least Once A Week	Frequent	58544	48.26
3	At Least Once A Month	Infrequent	26313	21.69
4	At Least Once A Year	Infrequent	7368	6.07
5	Never/Not Applicable	Infrequent	372	0.31
		Overall	121313	100
		Holiday driving		
0	Not answered	NA	8315	6.85
3	At Least Once A Month	Frequent	5969	4.92
4	At Least Once A Year	Frequent	94079	77.55
5	Never/Not Applicable	Infrequent	12950	10.67
		Overall	121313	100

clusters until it reaches the stopping criteria, producing a hierarchy of disjoint clusters. The cluster procedure stops splitting when every cluster has only one eigenvalue greater than one. In the analysis, the procedure stops after four clusters of variables. Approximately 54.4% of the total variation is accounted for by the four cluster components (column (3) in Table 3.13). The cluster summary (Table 3.14) gives the number of variables in each cluster and the variation explained by the cluster component. Table 3.15 provides an overview of variables that belong to each of four clusters. Here, the column labeled "R^2 with Own Cluster" gives the squared correlation of the variable with its own cluster component. This value should be higher than the squared correlation with any other cluster. A larger squared correlation is better. The column "R^2 with Next Closest" contains the next-highest squared correlation of the variable with a cluster component, and low values here suggest that the clusters are well separated. The column labeled "$1 - R^2$ Ratio" gives the ratio of one minus the "Own Cluster" R^2 to one minus the "Next Closest" R^2. A small "$1 - R^2$ Ratio" indicates good clustering. The cluster components are oblique. The intercluster correlation is presented in Table 3.16. The cluster structure in Table 3.17 contains the correlations between each variable and each cluster component, which are used to interpret the cluster components. The standardized scoring coefficients in Table 3.18 are used to compute the first principal component of each cluster. Since each variable is assigned to one and only one cluster, each row of the scoring coefficients contains only one nonzero value (zero values are removed for better readability).

Education level and hometown size were not included in the final clustering procedure because a cluster procedure with them resulted in these two determinants to be in their own cluster components. For ease of interpretation of the regression results, we multiplied the score values for the first and second cluster components by -1.

Table 3.13: Statistics for the clustering procedure

(1) Number of clusters	(2) Total variation explained	(3) Proportion of variation explained	(4) Minimum proportion explained	(5) Maximum second eigenvalue	(6) Minimum R-squared	(7) Maximum $1 - R^2$ ratio
1	2.183	0.218	0.218	1.265	0.067	
2	3.391	0.339	0.244	1.160	0.073	0.934
3	4.476	0.448	0.296	1.017	0.143	0.861
4	5.440	0.544	0.400	0.959	0.215	0.804

Table 3.14: Cluster summary for 4 clusters

Cluster	Members	Cluster variation	Variation explained	Proportion explained	Second eigenvalue
1	4	4	1.602	0.400	0.959
2	2	2	1.439	0.720	0.561
3	2	2	1.261	0.631	0.739
4	2	2	1.138	0.569	0.862

Table 3.15: Cluster description

Cluster	Variable		R^2 with own cluster	R^2 with next closest	$1 - R^2$ ratio
Cluster 1	Gender	(Male=1, Female=2)	0.215	0.024	0.804
	Age	(number)	0.683	0.075	0.342
	Children under 18	(number)	0.408	0.032	0.612
	Financing method	(Savings=1, Loan=2)	0.295	0.005	0.708
Cluster 2	Frequent holiday trips	(Yes=1, No=2)	0.720	0.036	0.291
	Frequent weekend trips	(Yes=1, No=2)	0.720	0.044	0.293
Cluster 3	Net monthly income	(group)	0.631	0.007	0.372
	Two cars or more	(Yes=1, No=2)	0.631	0.077	0.400
Cluster 4	Considered a used car	(Yes=1, No=2)	0.569	0.047	0.452
	Same make as previous	(Yes=1, No=2)	0.569	0.022	0.441

Table 3.16: Inter-cluster correlations

Cluster	1	2	3	4
1	1	0.234	0.219	-0.241
2	0.234	1	0.143	-0.063
3	0.219	0.143	1	-0.067
4	-0.241	-0.063	-0.067	1

Table 3.17: Cluster structure

Variable		Cluster 1	2	3	4
Gender	(Male=1, Female=2)	0.464	0.153	0.065	-0.065
Age	(number)	-0.827	-0.250	-0.207	0.273
Children under 18	(number)	0.639	0.094	0.179	-0.149
Net monthly income	(group)	0.071	0.083	0.794	-0.014
Financing method	(Savings=1, Loan=2)	0.543	0.068	0.066	-0.065
Considered a used car	(Yes=1, No=2)	-0.216	-0.050	-0.041	0.754
Frequent holiday trips	(Yes=1, No=2)	0.189	0.848	0.120	-0.044
Frequent weekend trips	(Yes=1, No=2)	0.209	0.848	0.123	-0.063
Two cars or more	(Yes=1, No=2)	-0.277	-0.145	-0.794	0.092
Same make as previous	(Yes=1, No=2)	0.148	0.045	0.060	-0.754

Table 3.18: Standardized scoring coefficients

Variable		Cluster 1	2	3	4
Gender	(Male=1, Female=2)	0.290			
Age	(number)	-0.516			
Children under 18	(number)	0.399			
Net monthly income	(group)			0.630	
Financing method	(Savings=1, Loan=2)	0.339			
Considered a used car	(Yes=1, No=2)				0.663
Frequent holiday trips	(Yes=1, No=2)		0.589		
Frequent weekend trips	(Yes=1, No=2)		0.589		
Two cars or more	(Yes=1, No=2)			-0.630	
Same make as previous	(Yes=1, No=2)				-0.663

3.7.C Additional tables

Table 3.19: The number of observations and length of ownership by type of previous car

	N	New			Used	
		Share	Length, months		Length, months	
			Mean (SD)	Median	Mean (SD)	Median
			Diesel vehicles			
Minis	234	0.57	71.00 (43.10)	60	56.90 (35.09)	52
Superminis	4134	0.58	67.72 (40.94)	60	55.67 (35.22)	48
Compact class	14884	0.64	65.20 (38.29)	59	59.46 (36.03)	51
Middle class	14328	0.67	63.66 (36.83)	56	60.30 (35.01)	54
Upper middle class	4869	0.72	62.77 (38.52)	54	62.38 (37.58)	56
Upper class	312	0.75	63.35 (42.15)	52	54.33 (39.10)	48
Over car classes	38761	0.65	64.53 (38.13)	57	59.50 (35.78)	51
			Gasoline vehicles			
Minis	3924	0.52	81.01 (48.36)	72	63.13 (40.80)	54
Superminis	19824	0.63	79.87 (44.43)	72	66.41 (39.68)	60
Compact class	33232	0.70	73.05 (39.41)	64	66.77 (37.82)	60
Middle class	20832	0.74	66.60 (36.48)	60	66.31 (37.07)	60
Upper middle class	4383	0.79	65.20 (35.08)	60	65.03 (37.41)	60
Upper class	357	0.82	62.50 (32.63)	60	57.51 (31.08)	54
Over car classes	82552	0.69	72.54 (40.23)	62	66.22 (38.42)	60

NOTE: The share of previous cars that are used is one minus the share of previous vehicles that are new.

Table 3.20: Overview of the selected studies on consumer valuation of future fuel costs based on revealed preference data

Study	Framework	Dependent Variable	Market	Data level	Time period	Fuel efficiency measure	Transaction prices	Taste heterogeneity	KM heterogeneity	Holding heterogeneity	Results on valuation
Ohta and Griliches (1986)	Hedonic demand	vehicle prices	used	aggregate	1966-1980	1/MPG	no	no	no	no	just
Kahn (1986)	Price regression	vehicle prices	used	aggregate	1971-1981	PVFC	no	no	no	no	under
Arguea et al. (1994)	Hedonic demand	vehicle prices	new	aggregate	1969-1986	MPG	no	no	no	no	under
Dreyfus and Viscusi (1995)	Price regression	vehicle prices	new & used	individual	1988	PVFC	no	no	no	no	just
Goldberg (1995)	Discrete choice	vehicle choices	new	individual	1983-1987	FP/MPG	no	yes	no	no	just
Berry et al. (1995)	Discrete choice	sales shares	new	aggregate	1971-1990	MPG/FP	no	yes	no	no	under
Goldberg (1998)	Discrete choice	vehicle choices	new	individual	1984-1990	FP/MPG	no	yes	no	no	just
Espey and Nair (2005)	Price regression	vehicle prices	new	aggregate	2001	1/MPG	no	no	no	no	just
Train and Winston (2007)	Discrete choice	vehicle choices	new	aggregate	2000	1/MPG	no	yes	no	no	under
Fan and Rubin (2010)	Hedonic demand	vehicle prices	new	aggregate	2007	log(MPG)	no	yes	no	no	under
Busse et al. (2013)	Sales & price regression	sales shares & vehicle prices	new & used	aggregate	1999-2008	MPG quantiles	yes	yes	no	no	just

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Study	Framework	Dependent Variable	Market	Data level	Time period	Fuel efficiency measure	Transaction prices	Taste heterogeneity	KM heterogeneity	Holding heterogeneity	Results on valuation
Allcott and Wozny (2014)	Price regression	vehicle prices	new & used	aggregate	1999-2008	PVFC	yes	no	no	no	under
Sallee et al. (2016)	Price regression	vehicle prices	used	individual	1990-2009	PVFC	yes	yes	yes	no	just
Grigolon et al. (2017)	Discrete choice	sales shares	new	aggregate	1998-2011	PVFC	no	yes	yes	no	just
Current study	Hedonic discrete choice	vehicle prices	new	individual	2000-2006	PVFC	yes	yes	yes	yes	under

Table 3.21: Quantile regression results for undervaluation of fuel savings on a set of consumer-related characteristics

Variable	OLS	Q10	Q25	Q50	Q75	Q90
Intercept	83.95***	71.76***	81.04***	82.84***	86.98***	94.14***
	(1.09)	(3.20)	(1.48)	(1.05)	(0.84)	(0.86)
Gender (NA)	-0.94	-0.57	-0.82	-0.59	-1.18	-0.88
	(1.19)	(4.55)	(1.00)	(0.84)	(0.85)	(1.10)
Gender (Male)	-0.26***	-0.78***	-0.52***	-0.15**	0.00	-0.04
	(0.09)	(0.19)	(0.11)	(0.07)	(0.07)	(0.05)
Age	-0.01***	-0.02***	-0.02***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Children under 18	0.00	0.17*	-0.07	-0.12***	-0.14***	-0.11***
	(0.05)	(0.10)	(0.07)	(0.05)	(0.04)	(0.04)
Town size	-0.10***	-0.15***	-0.06***	-0.04**	-0.03**	-0.01
	(0.02)	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)
University degree (NA)	-6.33	2.66	-9.39	-5.86	-2.66	-6.59
	(8.16)	(134.08)	(17.75)	(16.54)	(13.57)	(26.43)
University degree (yes)	-4.33***	-5.69*	-3.55*	-3.67***	-2.75***	-2.47***
	(1.13)	(3.32)	(2.04)	(1.07)	(1.01)	(0.78)
Financing (NA)	0.30	0.55	0.39**	0.18	-0.02	0.02
	(0.18)	(0.37)	(0.19)	(0.14)	(0.12)	(0.12)
Financing (Savings)	0.49***	0.85***	0.47***	0.31***	0.15**	0.07
	(0.08)	(0.17)	(0.09)	(0.07)	(0.06)	(0.06)
Cons. used car (NA)	-0.85**	-1.58*	-1.00**	-0.57**	-0.27	-0.56***
	(0.34)	(0.82)	(0.48)	(0.27)	(0.27)	(0.19)
Cons. used car (yes)	0.68***	1.56***	0.71***	0.39***	0.20***	0.04
	(0.08)	(0.17)	(0.09)	(0.06)	(0.06)	(0.05)
Income (NA)	0.38	1.06	0.66	-0.27	0.12	-0.05
	(0.81)	(2.03)	(1.14)	(0.68)	(0.51)	(0.59)
Income (under 1000)	0.52	1.52	0.89	-0.42	-0.02	-0.04
	(0.88)	(2.16)	(1.12)	(0.70)	(0.57)	(0.66)
Income (€1000-€1249)	0.65	1.48	1.00	-0.36	0.10	-0.24
	(0.84)	(2.03)	(1.13)	(0.68)	(0.54)	(0.58)
Income (€1250-€1499)	0.86	1.64	1.12	0.01	0.21	-0.05
	(0.83)	(1.98)	(1.09)	(0.68)	(0.51)	(0.61)
Income (€1500-€1749)	0.81	1.59	0.86	-0.03	0.17	-0.07
	(0.82)	(2.03)	(1.14)	(0.68)	(0.51)	(0.60)
Income (€1750-€1999)	0.93	2.10	1.37	0.00	0.20	-0.07
	(0.82)	(1.98)	(1.13)	(0.68)	(0.49)	(0.58)
Income (€2000-€2249)	0.50	1.02	0.70	-0.39	0.03	-0.01
	(0.82)	(2.01)	(1.12)	(0.67)	(0.51)	(0.61)
Income (€2250-€2499)	0.55	1.06	0.92	-0.23	0.03	-0.12
	(0.82)	(2.01)	(1.14)	(0.69)	(0.51)	(0.59)
Income (€2500-€2999)	0.09	0.46	0.38	-0.54	-0.20	-0.11
	(0.81)	(2.03)	(1.11)	(0.68)	(0.51)	(0.59)
Income (€3000-€3499)	0.21	0.51	0.50	-0.43	-0.01	-0.10
	(0.81)	(2.03)	(1.14)	(0.69)	(0.52)	(0.60)
Income (€3500-€3999)	0.02	-0.15	0.34	-0.18	0.13	0.04
	(0.81)	(2.03)	(1.13)	(0.68)	(0.51)	(0.58)
Income (€4000-€4999)	-0.95	-1.98	-0.61	-1.02	-0.33	-0.10
	(0.82)	(2.04)	(1.15)	(0.68)	(0.52)	(0.59)
Income (€5000-€7499)	-1.33	-3.03	-0.98	-0.96	0.01	-0.08
	(0.84)	(2.30)	(1.22)	(0.73)	(0.54)	(0.62)
Income (€7500-€9999)	-2.49***	-4.78	-3.29**	-2.11*	-0.81	0.04
	(0.95)	(3.01)	(1.50)	(1.10)	(0.70)	(0.79)
Income (€10000-€14999)	-1.72	-7.49*	-1.52	-1.78	-0.59	0.48
	(1.13)	(4.40)	(1.61)	(1.26)	(1.07)	(0.92)
Income (NA) x Uni (NA)	6.06	-3.72	9.29	5.74	2.74	6.21
	(8.17)	(133.98)	(17.77)	(16.52)	(13.57)	(26.41)
Income (NA) x Uni (yes)	4.36***	5.50	3.48*	3.82***	3.14***	2.92***
	(1.16)	(3.36)	(2.07)	(1.11)	(1.05)	(0.80)
Income (under €1000) x Uni (NA)	2.21	-15.81	6.07	2.30	2.87	5.40
	(8.60)	(135.14)	(19.13)	(16.86)	(13.71)	(27.68)
Income (under €1000) x Uni (yes)	4.74***	7.03*	3.34	4.25***	1.91	1.85
	(1.70)	(4.15)	(2.28)	(1.31)	(1.35)	(1.20)
Income (€1000-€1249) x Uni (NA)	2.09	-23.29	1.91	3.62	4.56	8.90
	(8.56)	(134.14)	(18.98)	(17.02)	(13.59)	(26.52)
Income (€1000-€1249) x Uni (yes)	4.00***	5.89	2.75	3.08**	3.00**	2.97***
	(1.44)	(3.87)	(2.29)	(1.20)	(1.26)	(0.90)
Income (€1250-€1499) x Uni (NA)	5.92	-5.25	8.20	5.32	1.99	5.14
	(8.43)	(133.42)	(17.66)	(16.44)	(13.38)	(26.36)
Income (€1250-€1499) x Uni(yes)	4.22***	5.14	3.74*	3.77***	3.37***	2.73***
	(1.29)	(3.34)	(2.06)	(1.11)	(1.09)	(0.95)

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Variable	OLS	Q10	Q25	Q50	Q75	Q90
Income (€1500-€1749) x Uni (NA)	2.99	-11.62	6.05	3.80	1.43	6.57
	(8.40)	(133.74)	(17.93)	(16.46)	(13.63)	(26.35)
Income (€1500-€1749) x Uni (yes)	4.09***	5.02	2.92	3.25***	2.21**	2.57***
	(1.24)	(3.38)	(2.18)	(1.11)	(1.05)	(0.82)
Income (€1750-€1999) x Uni (NA)	6.81	-3.47	9.94	6.18	3.00	7.69
	(8.32)	(134.10)	(17.68)	(16.51)	(13.60)	(26.32)
Income (€1750-€1999) x Uni (yes)	4.31***	5.42	3.29	3.45***	2.53**	2.40***
	(1.19)	(3.32)	(2.06)	(1.09)	(1.01)	(0.83)
Income (€2000-€2249) x Uni (NA)	6.45	-3.49	9.24	3.31	1.73	6.04
	(8.33)	(133.54)	(17.75)	(16.54)	(13.62)	(26.45)
Income (€2000-€2249) x Uni (yes)	4.59***	6.27*	3.68*	3.87***	2.81***	2.49***
	(1.18)	(3.31)	(2.04)	(1.09)	(1.01)	(0.82)
Income (€2250-€2499) x Uni (NA)	4.02	-4.70	5.90	3.32	2.10	5.48
	(8.31)	(134.10)	(17.97)	(16.40)	(13.63)	(26.15)
Income (€2250-€2499) x Uni (yes)	4.57***	5.43	3.65*	3.68***	3.16***	2.67***
	(1.18)	(3.41)	(2.08)	(1.14)	(1.05)	(0.79)
Income (€2500-€2999) x Uni (NA)	8.62	-2.18	12.20	6.49	3.77	7.31
	(8.30)	(133.49)	(17.88)	(16.42)	(13.39)	(26.30)
Income (€2500-€2999) x Uni (yes)	4.61***	6.41*	4.38**	4.12***	3.27***	2.81***
	(1.16)	(3.33)	(2.07)	(1.09)	(1.02)	(0.80)
Income (€3000-€3499) x Uni (NA)	4.12	-11.05	4.86	3.37	3.06	6.89
	(8.27)	(133.26)	(17.82)	(16.72)	(13.56)	(26.39)
Income (€3000-€3499) x Uni (yes)	4.79***	6.94**	3.96*	3.91***	2.89***	2.61***
	(1.15)	(3.33)	(2.04)	(1.09)	(1.00)	(0.81)
Income (€3500-€3999) x Uni (NA)	6.06	-3.16	9.25	6.02	2.28	7.09
	(8.32)	(134.61)	(17.69)	(16.24)	(13.42)	(26.26)
Income (€3500-€3999) x Uni (yes)	4.79***	7.10**	4.03*	3.62***	2.83***	2.58***
	(1.15)	(3.32)	(2.06)	(1.06)	(1.02)	(0.78)
Income (€4000-€4999) x Uni (NA)	8.35	3.44	11.44	6.30	3.05	6.17
	(8.48)	(133.67)	(17.69)	(16.70)	(13.58)	(26.22)
Income (€4000-€4999) x Uni (yes)	5.52***	8.21**	4.82**	4.29***	3.23***	2.72***
	(1.16)	(3.45)	(2.12)	(1.10)	(1.05)	(0.80)
Income (€5000-€7499) x Uni (NA)	10.79	5.15	8.21	9.41	5.17	9.05
	(8.72)	(133.24)	(17.24)	(17.07)	(14.09)	(28.25)
Income (€5000-€7499) x Uni (yes)	4.73***	7.40**	3.71*	3.24***	2.52**	2.30***
	(1.18)	(3.62)	(2.13)	(1.10)	(1.01)	(0.83)
Income (€7500-€9999) x Uni (NA)	5.78	14.33	14.16	2.34	-2.39	-3.09
	(11.52)	(710.55)	(90.14)	(54.90)	(53.32)	(168.40)
Income (€7500-€9999) x Uni (yes)	4.60***	5.61	5.40**	3.76**	3.49***	2.00**
	(1.33)	(4.06)	(2.28)	(1.56)	(1.23)	(0.95)
Income (€10000-€14999) x Uni (NA)	-5.85	-18.28	-17.06	-6.58	3.12	5.86
	(10.01)	(317.22)	(47.36)	(36.40)	(29.22)	(45.11)
Income (€10000-€14999) x Uni (yes)	2.61*	10.52	3.85	3.04	2.08	0.02
	(1.54)	(6.55)	(2.40)	(1.95)	(1.53)	(1.23)
Multiple cars	-0.21**	-0.22	-0.18	-0.03	-0.06	-0.10*
	(0.09)	(0.20)	(0.11)	(0.07)	(0.06)	(0.06)
Holiday (NA)	-0.03	0.06	-0.17	-0.20	-0.29**	-0.07
	(0.21)	(0.41)	(0.22)	(0.13)	(0.14)	(0.14)
Holiday (Frequent usage)	-0.29**	-0.65***	-0.54***	-0.35***	-0.21**	-0.09
	(0.13)	(0.24)	(0.13)	(0.09)	(0.09)	(0.08)
Weekend (NA)	0.00	-0.02	0.11	0.01	0.14	0.20*
	(0.15)	(0.35)	(0.18)	(0.12)	(0.11)	(0.10)
Weekend (Frequent usage)	-0.24***	-0.55***	-0.31***	-0.07	-0.04	0.04
	(0.09)	(0.17)	(0.11)	(0.06)	(0.06)	(0.05)
Same make as previous (NA)	0.19	-0.17	-0.59	-0.54	0.37	-0.38
	(0.86)	(1.59)	(0.68)	(0.63)	(0.67)	(0.45)
Same make as previous (yes)	0.15*	0.69***	0.06	-0.07	-0.20***	-0.20***
	(0.08)	(0.16)	(0.09)	(0.06)	(0.05)	(0.05)
Expected KM (000)	-0.04***	-0.11***	-0.04***	-0.02**	0.00	0.00
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)
Fuel price	-10.09***	-22.22***	-13.66***	-7.10***	-2.73***	-0.72**
	(0.41)	(1.10)	(0.53)	(0.34)	(0.33)	(0.30)
Engine type dummies	Yes	Yes	Yes	Yes	Yes	Yes
Car class dummies	Yes	Yes	Yes	Yes	Yes	Yes

NOTE: The table reports the results of a quantile regression on the initial (non-standardized) consumer-specific determinants. Each coefficient, $\gamma_d(\tau)$, shows a change in the conditional quantile of the undervaluation (in € cents) as the explanatory variable increases by one unit, ceteris paribus. The reference category is female; upper class; university degree (no); financing (loan); considered a used car (no); one car in the household; same make as previous (no); holiday trips (infrequent usage); and weekend trips (infrequent usage). Standard errors are in parentheses. The number of observations used is 98873. *p<0.1; **p<0.05; ***p<0.01.

Table 3.22: Quantile regression results for undervaluation of fuel savings on clustered variables

Variable	OLS	Q10	Q25	Q50	Q75	Q90
Cluster 1	-0.27***	-0.76***	-0.30***	-0.08	-0.01	-0.04
(Socio-economic status)	(0.08)	(0.18)	(0.10)	(0.07)	(0.07)	(0.05)
Cluster 2	-0.14*	-0.26	-0.24***	-0.16***	-0.09*	0.02
(Recreational diving)	(0.08)	(0.16)	(0.09)	(0.06)	(0.05)	(0.05)
Cluster 3	-0.89***	-1.62***	-0.72***	-0.38***	-0.20***	-0.09*
(Financial ability)	(0.08)	(0.17)	(0.10)	(0.06)	(0.06)	(0.05)
Cluster 4	-0.31***	-0.63***	-0.39***	-0.34***	-0.27***	-0.16***
(Consideration process)	(0.08)	(0.17)	(0.09)	(0.06)	(0.06)	(0.05)
Town size	-0.51***	-0.80***	-0.41***	-0.19***	-0.11**	-0.02
	(0.07)	(0.17)	(0.09)	(0.05)	(0.05)	(0.05)
University degree (NA)	-0.66*	-2.07***	-1.00**	-0.42	0.00	-0.28
	(0.34)	(0.77)	(0.46)	(0.33)	(0.27)	(0.20)
University degree (yes)	0.14	0.39*	0.13	0.01	0.12*	0.12**
	(0.09)	(0.21)	(0.12)	(0.07)	(0.07)	(0.06)
Expected KM ('000)	-0.62***	-1.67***	-0.69***	-0.23***	0.01	0.04
	(0.09)	(0.19)	(0.13)	(0.08)	(0.08)	(0.07)
Fuel price	-2.66***	-5.67***	-3.57***	-1.85***	-0.73***	-0.19***
	(0.10)	(0.31)	(0.13)	(0.08)	(0.08)	(0.07)
Intercept	69.58***	40.14***	61.60***	72.13***	82.68***	92.82***
	(0.53)	(2.11)	(1.07)	(0.80)	(0.68)	(0.51)
Engine type dummies	Yes	Yes	Yes	Yes	Yes	Yes
Car class dummies	Yes	Yes	Yes	Yes	Yes	Yes

NOTE: The table reports the results of a quantile regression on the clustered and standardized variables. Each coefficient, $\gamma_d(\tau)$, shows a change in the conditional quantile of the undervaluation (in € cents) as the explanatory variable increases by two standard deviations, ceteris paribus. The reference category is given by upper class; diesel; and no university degree. Standard errors are in parentheses. The number of observations used is 98873. *p<0.1; **p<0.05; ***p<0.01.

Table 3.23: The valuation parameter under alternative assumptions

			Diesel		Gasoline	
			β	SD	β	SD
Parametric regression						
Over car classes, base		(1)	0.09	0.03	0.09	0.04
By car class, base		(2)	0.09	0.02	0.09	0.02
Nonparametric regression						
Over car classes, base		(3)	0.15	0.12	0.11	0.10
By car class, base		(4)	0.17	0.15	0.13	0.13
By car class, interest rate						
	r=10%	(5)	0.20	0.17	0.16	0.15
	r=15%	(6)	0.22	0.20	0.19	0.18
By car class, length of ownership						
	T=10 years	(7)	0.11	0.14	0.11	0.14
	T=15 years	(8)	0.08	0.10	0.08	0.10
	T for only new prev.car	(9)	0.16	0.13	0.12	0.11
By car class, Grigolon et al. (2017)'s assumptions	T=15; r=6%	(10)	0.08	0.09	0.07	0.08
By car class, time period	2005-2006	(11)	0.18	0.11	0.13	0.08

NOTE: The table presents the estimated valuation parameters (β) based on the hedonic price regression in Equation 3.7 under alternative assumptions. In the case of separate estimations by car class, the weighted averages are displayed. “Base” corresponds to the assumptions of the length of ownership being approximated by that of the previous car in possession and an interest rate of 3%. Unless otherwise stated, all specifications include 121313 observations. For (9), there are 82317 observations. For (11), there are 37001 observations.

Table 3.24: Descriptive statistics for vehicle attributes

			Minis	Superminis	Compact class	Middle class	Upper middle class	Upper class
					Diesel vehicles (N=38761)			
Purchase price	2010€	Mean	15,877.34	18,256.44	25,033.25	32,242.05	45,261.52	63,792.14
		SD	2,079.97	2,708.01	4,030.41	5,681.84	9,367.14	18,389.00
Fuel consumption	l/100km	Mean	4.60	4.68	5.57	6.49	8.20	10.26
		SD	0.57	0.37	0.52	0.89	1.48	1.28
Fuel economy	km/l	Mean	22.17	21.50	18.11	15.67	12.60	9.91
		SD	3.45	1.90	1.62	1.91	2.29	1.36
Horse power	HP	Mean	70.55	85.50	111.99	130.03	163.34	192.22
		SD	3.69	16.39	19.72	20.97	29.29	34.92
Displacement	cm^3	Mean	1,323.79	1,563.28	1,881.24	2,060.10	2,539.62	3,147.84
		SD	92.65	240.12	153.33	227.37	355.49	463.61
Weight	kg	Mean	1,465.93	1,608.44	1,872.49	2,134.40	2,416.53	2,905.79
		SD	94.53	108.53	137.48	212.59	304.27	272.88
Power per weight	HP/ton	Mean	48.28	53.02	59.77	61.39	68.41	67.22
		SD	3.30	8.63	9.31	10.86	13.60	16.32
Automatic transmission	0/1	Mean	0.01	0.03	0.09	0.15	0.57	0.71
		SD	0.11	0.18	0.28	0.36	0.49	0.46
Number of consumers		N	234	4134	14884	14328	4869	312
Examples of vehicles			Citroen C1 Ford Ka Opel Agila Toyota Aygo VW Lupo	Audi A2/S2 Citroen C2 Ford Fiesta Opel Corsa Toyota Yaris VW Polo	Audi A3/S3 BMW 1 Series Citroen C4 Ford Focus Mercedes A, B Opel Astra Toyota Corolla VW Golf	Audi A4/RS4/S4 BMW 3 Series Citroen C5 Ford Mondeo Mercedes C Opel Vectra Toyota Avensis VW Passat	Audi A6/S6 BMW 5 Series Mercedes E Opel Signum Toyota Camry VW Touareg	Audi A8 BMW 7 Series Mercedes S VW Phaeton

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			Minis	Superminis	Compact class	Middle class	Upper middle class	Upper class
			Gasoline vehicles (N=82552)					
Purchase price	2010€	Mean	12,134.06	15,791.04	21,577.83	28,639.61	43,741.01	82,665.92
		SD	2,371.53	2,905.93	3,842.69	6,235.92	11,615.09	20,442.22
Fuel consumption	l/100km	Mean	5.95	6.36	7.40	8.61	10.23	12.19
		SD	0.54	0.57	0.72	1.10	1.44	1.39
Fuel economy	km/l	Mean	16.96	15.84	13.64	11.79	9.95	8.30
		SD	1.68	1.36	1.26	1.39	1.31	0.85
Horse power	HP	Mean	63.19	79.24	108.71	138.59	184.01	280.46
		SD	10.71	17.52	19.82	27.31	42.66	52.28
Displacement	cm^3	Mean	1,161.51	1,337.98	1,645.41	2,008.60	2,656.14	3,987.93
		SD	156.12	178.85	208.71	333.63	590.35	762.01
Weight	kg	Mean	1,307.88	1,509.16	1,734.13	1,948.85	2,134.23	2,491.23
		SD	95.42	100.44	121.67	157.21	178.68	235.18
Power per weight	HP/ton	Mean	48.38	52.36	62.61	71.13	85.86	112.89
		SD	7.53	10.32	10.10	12.64	16.70	19.93
Automatic transmission	0/1	Mean	0.05	0.10	0.12	0.21	0.59	0.96
		SD	0.22	0.30	0.33	0.41	0.49	0.21
Number of consumers		N	3924	19824	33232	20832	4383	357
Examples of vehicles			Citroen C1 Ford Ka Opel Agila Toyota Aygo VW Lupo	Audi A2/S2 Citroen C2 Ford Fiesta Opel Corsa Toyota Yaris VW Polo	Audi A3/S3 BMW 1 Series Citroen C4 Ford Focus Mercedes A, B Opel Astra Toyota Corolla VW Golf	Audi A4/RS4/S4 BMW 3 Series Citroen C5 Ford Mondeo Mercedes C Opel Vectra Toyota Avensis VW Passat	Audi A6/S6 BMW 5 Series Mercedes E Opel Signum Toyota Camry VW Touareg	Audi A8 BMW 7 Series Mercedes S VW Phaeton

NOTE: Fuel consumption, weight, and car class are retrieved from the ADAC web database (http://www.adac.de/infotestrat/autodatenbank) and matched to the transaction data. All monetary values in the data are inflation-adjusted by using the consumer price index (CPI), which is normalized to one in April 2010.

Table 3.25: Descriptive statistics for the nonparametric hedonic price regression estimates

		Diesel vehicles					Gasoline vehicles				
		Mean	SE	P10	Median	P90	Mean	SE	P10	Median	P90
PVFC (Estimate)	Minis	-2.09E-06	8.05E-07	-1.70E-05	1.76E-06	8.97E-06	-8.65E-06	1.18E-07	-1.80E-05	-8.70E-06	3.84E-07
PVFC (SE)		2.22E-09	8.22E-11	1.18E-09	1.92E-09	3.47E-09	1.21E-10	8.80E-13	6.92E-11	1.07E-10	1.87E-10
PVFC (Estimate)	Superminis	-6.08E-06	8.73E-08	-1.22E-05	-5.80E-06	-8.24E-08	-4.52E-06	3.78E-08	-9.40E-06	-4.78E-06	8.36E-07
PVFC (SE)		3.99E-11	3.07E-13	2.39E-11	3.39E-11	6.38E-11	2.99E-11	1.55E-13	1.53E-11	2.25E-11	5.41E-11
PVFC (Estimate)	Compact class	-3.84E-06	4.49E-08	-9.63E-06	-4.02E-06	2.11E-06	-4.16E-06	3.10E-08	-1.03E-05	-3.93E-06	1.59E-06
PVFC (SE)		1.72E-11	9.16E-14	6.67E-12	1.38E-11	3.27E-11	1.48E-11	5.63E-14	6.02E-12	1.14E-11	2.85E-11
PVFC (Estimate)	Middle class	-3.93E-06	5.04E-08	-1.06E-05	-4.05E-06	2.73E-06	-3.57E-06	4.40E-08	-1.03E-05	-3.48E-06	3.03E-06
PVFC (SE)		2.25E-11	1.05E-13	9.58E-12	1.96E-11	4.02E-11	1.59E-11	7.83E-14	5.26E-12	1.23E-11	3.20E-11
PVFC (Estimate)	Upper middle class	-3.23E-06	7.97E-08	-9.22E-06	-3.10E-06	2.77E-06	-2.57E-06	7.61E-08	-8.36E-06	-2.49E-06	2.88E-06
PVFC (SE)		3.22E-11	2.17E-13	1.72E-11	2.82E-11	5.21E-11	4.14E-11	3.55E-13	1.74E-11	3.57E-11	7.19E-11
PVFC (Estimate)	Upper class	-3.33E-06	3.96E-07	-1.25E-05	-3.47E-06	4.48E-06	-3.64E-06	3.65E-07	-1.04E-05	-3.24E-06	9.83E-07
PVFC (SE)		2.33E-10	6.94E-12	1.12E-10	1.98E-10	3.98E-10	2.23E-10	6.36E-12	1.19E-10	1.69E-10	3.44E-10
HPW (Estimate)	Minis	-1.26E-02	4.43E-03	-1.21E-01	-8.80E-04	5.67E-02	9.69E-03	5.18E-05	6.25E-03	9.39E-03	1.35E-02
HPW (SE)		2.85E-06	1.06E-07	1.52E-06	2.47E-06	4.46E-06	1.67E-08	1.21E-10	9.52E-09	1.47E-08	2.57E-08
HPW (Estimate)	Superminis	5.85E-03	3.68E-05	2.74E-03	6.15E-03	8.28E-03	9.18E-03	1.20E-05	7.25E-03	9.28E-03	1.10E-02
HPW (SE)		2.20E-08	1.69E-10	1.32E-08	1.87E-08	3.52E-08	8.32E-09	4.31E-11	4.24E-09	6.25E-09	1.51E-08
HPW (Estimate)	Compact class	6.17E-03	1.75E-05	4.00E-03	6.25E-03	8.27E-03	7.28E-03	1.17E-05	5.00E-03	7.22E-03	9.72E-03
HPW (SE)		5.37E-09	2.86E-11	2.09E-09	4.32E-09	1.02E-08	7.01E-09	2.67E-11	2.86E-09	5.41E-09	1.35E-08
HPW (Estimate)	Middle class	7.51E-03	2.04E-05	4.64E-03	7.45E-03	1.04E-02	7.45E-03	1.78E-05	4.70E-03	7.37E-03	1.06E-02
HPW (SE)		5.35E-09	2.50E-11	2.28E-09	4.66E-09	9.56E-09	5.34E-09	2.63E-11	1.76E-09	4.14E-09	1.08E-08
HPW (Estimate)	Upper middle class	8.44E-03	4.89E-05	3.73E-03	8.34E-03	1.29E-02	7.03E-03	3.10E-05	4.83E-03	6.92E-03	9.56E-03
HPW (SE)		1.24E-08	8.30E-11	6.59E-09	1.08E-08	2.00E-08	1.54E-08	1.32E-10	6.45E-09	1.32E-08	2.67E-08
HPW (Estimate)	Upper class	-2.49E-04	1.39E-03	-4.60E-02	5.17E-03	2.08E-02	7.80E-03	1.07E-04	5.54E-03	8.33E-03	9.73E-03
HPW (SE)		3.35E-01	9.95E-03	1.61E-01	2.85E-01	5.71E-01	1.10E-07	3.15E-09	5.88E-08	8.35E-08	1.71E-07
Weight (Estimate)	Minis	-4.21E-04	1.79E-04	-4.56E-03	-7.09E-04	2.64E-03	1.22E-03	4.18E-06	8.82E-04	1.19E-03	1.59E-03
Weight (SE)		3.46E-02	1.28E-03	1.85E-02	3.00E-02	5.41E-02	2.06E-09	1.49E-11	1.17E-09	1.81E-09	3.17E-09
Weight (Estimate)	Superminis	3.61E-04	4.49E-06	4.64E-05	4.08E-04	6.66E-04	7.03E-04	1.55E-06	4.79E-04	6.78E-04	9.81E-04
Weight (SE)		1.94E-09	1.49E-11	1.16E-09	1.65E-09	3.10E-09	1.83E-09	9.48E-12	9.32E-10	1.37E-09	3.31E-09
Weight (Estimate)	Compact class	4.51E-04	1.95E-06	1.55E-04	4.67E-04	7.28E-04	5.23E-04	1.58E-06	2.65E-04	5.36E-04	8.44E-04
Weight (SE)		1.20E-09	6.39E-12	4.65E-10	9.64E-10	2.28E-09	3.59E-04	1.37E-06	1.47E-04	2.78E-04	6.94E-04
Weight (Estimate)	Middle class	3.93E-04	1.32E-06	1.87E-04	4.01E-04	5.78E-04	4.68E-04	1.44E-06	2.43E-04	4.59E-04	6.99E-04
Weight (SE)		6.01E-10	2.81E-12	2.55E-10	5.23E-10	1.07E-09	5.40E-10	2.66E-12	1.78E-10	4.19E-10	1.09E-09
Weight (Estimate)	Upper middle class	3.41E-04	2.08E-06	1.41E-04	3.60E-04	5.07E-04	6.22E-04	4.13E-06	3.11E-04	6.19E-04	9.39E-04
Weight (SE)		6.84E-10	4.60E-12	3.65E-10	6.00E-10	1.11E-09	1.50E-03	1.29E-05	6.30E-04	1.29E-03	2.61E-03

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Table 3.25: Descriptive statistics for the nonparametric hedonic price regression estimates (cont'd)

		Diesel vehicles					Gasoline vehicles				
		Mean	SE	P10	Median	P90	Mean	SE	P10	Median	P90
Weight (Estimate)	Upper class	3.16E-04	2.40E-05	-8.95E-05	2.89E-04	9.08E-04	7.63E-05	1.76E-05	-3.04E-04	1.28E-04	4.16E-04
Weight (SE)		4.60E-09	1.37E-10	2.21E-09	3.91E-09	7.84E-09	4.86E-08	1.39E-09	2.59E-08	3.67E-08	7.50E-08
Displacement	Minis	3.95E-06	3.14E-06	-3.46E-05	4.05E-06	4.06E-05	-5.83E-05	3.46E-05	-1.61E-03	-2.14E-05	1.45E-03
	Superminis	6.75E-04	1.38E-04	-6.76E-03	-3.57E-04	7.54E-03	-2.99E-05	5.38E-05	-6.73E-03	-3.48E-04	7.07E-03
	Compact class	8.92E-04	3.68E-05	-1.31E-03	4.40E-04	4.00E-03	-3.47E-04	5.35E-05	-1.07E-02	7.54E-05	9.72E-03
	Middle class	-2.69E-03	1.34E-04	-1.65E-02	-2.22E-03	1.06E-02	-6.24E-04	8.71E-05	-1.15E-02	-5.04E-04	1.02E-02
	Upper middle class	-2.13E-03	2.37E-04	-1.60E-02	-9.72E-04	9.22E-03	2.29E-05	2.69E-04	-1.52E-02	9.01E-04	1.25E-02
	Upper class	-8.96E-05	2.94E-05	-6.62E-04	-2.04E-05	4.93E-04	4.09E-05	3.96E-05	-3.31E-04	5.82E-06	2.67E-04
Transmission	Minis	1.11E-04	1.57E-05	9.37E-05	9.62E-05	1.42E-04	2.14E-02	2.01E-03	-8.83E-03	1.59E-02	6.64E-02
	Superminis	1.48E-02	1.49E-03	1.03E-03	1.12E-02	3.79E-02	2.20E-02	6.15E-04	-8.90E-03	2.15E-02	5.04E-02
	Compact class	3.16E-02	7.57E-04	2.95E-03	2.82E-02	6.77E-02	4.10E-02	6.36E-04	-5.95E-04	3.91E-02	8.90E-02
	Middle class	5.15E-02	1.13E-03	-9.25E-03	5.42E-02	1.10E-01	2.47E-02	4.69E-04	-9.09E-03	2.33E-02	6.49E-02
	Upper middle class	1.54E-02	3.06E-04	-2.00E-03	1.32E-02	3.74E-02	1.75E-02	4.75E-04	-7.03E-03	1.39E-02	5.03E-02
	Upper class	2.00E-02	2.85E-03	-2.85E-03	1.71E-03	8.61E-02	2.74E-04	6.01E-05	-5.23E-04	5.75E-05	1.01E-03
Sunroof	Minis	4.42E-02	1.11E-02	-3.20E-02	2.79E-02	1.31E-01	8.42E-03	6.47E-04	-1.10E-02	6.25E-03	3.01E-02
	Superminis	1.32E-02	8.98E-04	-7.01E-03	1.10E-02	3.55E-02	1.73E-02	6.00E-04	-4.69E-03	1.18E-02	4.71E-02
	Compact class	1.57E-02	6.02E-04	-8.35E-03	1.25E-02	4.65E-02	1.88E-02	5.46E-04	-1.10E-02	1.60E-02	5.96E-02
	Middle class	2.10E-02	7.05E-04	-1.72E-02	1.94E-02	6.16E-02	2.98E-02	7.78E-04	-1.55E-02	2.79E-02	8.06E-02
	Upper middle class	1.62E-02	5.23E-04	-5.60E-03	1.51E-02	4.32E-02	1.17E-02	4.81E-04	-9.54E-03	1.23E-02	3.29E-02
	Upper class	2.93E-02	1.95E-03	-1.37E-03	2.55E-02	6.29E-02	1.10E-03	2.33E-04	-2.22E-03	1.42E-03	5.15E-03
Air conditioning	Minis	1.35E-01	1.05E-02	3.83E-02	1.38E-01	3.03E-01	2.92E-02	7.32E-04	-1.37E-03	3.17E-02	5.64E-02
	Superminis	-5.54E-03	3.01E-04	-2.57E-02	-4.89E-03	1.29E-02	5.63E-03	1.64E-04	-1.24E-02	5.23E-03	2.44E-02
	Compact class	-6.62E-03	1.89E-04	-3.05E-02	-4.47E-03	1.26E-02	-1.19E-02	2.28E-04	-4.71E-02	-9.53E-03	1.91E-02
	Middle class	-2.08E-02	3.00E-04	-5.38E-02	-1.85E-02	7.46E-03	-1.25E-02	2.90E-04	-4.46E-02	-9.05E-03	1.38E-02
	Upper middle class	-7.88E-03	3.40E-04	-3.00E-02	-5.05E-03	8.38E-03	-9.58E-03	5.04E-04	-3.38E-02	-9.05E-03	1.38E-02
	Upper class	9.21E-05	1.31E-04	-1.84E-03	-5.01E-09	2.15E-03	-2.00E-03	2.31E-04	-5.02E-03	-3.08E-03	2.28E-03
Cruise control	Minis	6.46E-02	7.12E-02	-2.85E-02	1.77E-02	2.05E-01	4.53E-03	2.77E-03	-1.33E-02	5.04E-03	2.24E-02
	Superminis	9.11E-03	7.24E-04	-9.22E-03	6.69E-03	2.92E-02	5.67E-03	8.94E-04	-2.92E-02	5.08E-03	4.40E-02
	Compact class	1.06E-02	2.40E-04	-6.83E-03	8.62E-03	2.99E-02	1.41E-02	3.40E-04	-1.53E-02	1.37E-02	4.31E-02
	Middle class	9.30E-03	2.64E-04	-1.58E-02	7.32E-03	3.73E-02	1.61E-02	3.10E-04	-1.09E-02	1.27E-02	5.00E-02
	Upper middle class	2.85E-02	6.55E-04	-1.42E-02	2.22E-02	8.35E-02	1.27E-02	3.94E-04	-8.20E-03	8.52E-03	4.31E-02
	Upper class	5.20E-04	8.18E-05	-3.81E-04	6.68E-10	2.33E-03	2.57E-04	6.84E-05	-6.88E-04	7.02E-05	1.05E-03

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		Diesel vehicles					Gasoline vehicles				
		Mean	SE	P10	Median	P90	Mean	SE	P10	Median	P90
Leather seats	Minis	3.31E-04	3.44E-04	-1.31E-05	3.31E-04	6.75E-04	3.07E-02	1.83E-03	7.12E-03	2.90E-02	5.63E-02
	Superminis	8.39E-02	4.93E-03	9.49E-03	8.45E-02	1.48E-01	5.97E-02	2.52E-03	-1.09E-02	6.90E-02	1.28E-01
	Compact class	8.15E-02	1.85E-03	8.15E-03	7.73E-02	1.62E-01	4.14E-02	1.28E-03	-1.38E-02	3.50E-02	1.08E-01
	Middle class	4.62E-02	9.90E-04	-1.68E-02	4.79E-02	1.07E-01	2.97E-02	1.00E-03	-3.93E-02	3.08E-02	9.43E-02
	Upper middle class	1.57E-02	3.84E-04	-3.61E-03	1.39E-02	4.00E-02	6.72E-03	4.81E-04	-1.44E-02	4.67E-03	3.01E-02
	Upper class	6.10E-03	6.43E-04	-2.82E-03	4.01E-03	1.58E-02	-1.40E-03	1.34E-03	-1.83E-02	-6.22E-03	1.98E-02
GPS navigation	Minis	8.64E-02	5.50E-02	3.26E-03	6.54E-02	1.90E-01	1.40E-02	4.15E-03	-8.54E-03	1.28E-02	4.24E-02
	Superminis	1.56E-02	1.91E-03	-4.03E-03	1.14E-02	3.75E-02	2.23E-02	2.19E-03	-2.09E-02	1.44E-02	8.18E-02
	Compact class	4.85E-02	1.41E-03	-7.82E-03	4.60E-02	1.15E-01	5.21E-02	1.72E-03	-1.92E-02	5.20E-02	1.36E-01
	Middle class	2.94E-02	6.22E-04	-5.32E-03	2.88E-02	6.61E-02	4.62E-02	1.08E-03	-1.74E-02	4.66E-02	1.11E-01
	Upper middle class	2.48E-02	3.97E-04	4.35E-03	2.44E-02	4.63E-02	2.62E-02	6.79E-04	-4.51E-03	2.89E-02	5.67E-02
	Upper class	1.46E-02	1.49E-03	-3.46E-03	1.02E-02	4.04E-02	3.57E-03	3.55E-04	-1.50E-03	1.51E-03	1.10E-02
Park distance sensor	Minis	-1.03E-04	3.77E-05	-3.67E-04	-9.71E-05	3.32E-05	3.16E-03	3.13E-03	-2.01E-02	-1.77E-03	2.70E-02
	Superminis	1.28E-02	1.37E-03	-1.51E-02	1.45E-02	4.21E-02	6.41E-02	2.19E-03	-1.71E-02	5.98E-02	1.57E-01
	Compact class	1.68E-02	4.38E-04	-8.79E-03	1.47E-02	5.00E-02	1.92E-02	4.39E-04	-1.06E-02	1.54E-02	5.82E-02
	Middle class	1.24E-02	3.22E-04	-1.48E-02	1.24E-02	3.97E-02	1.70E-02	3.81E-04	-1.41E-02	1.60E-02	5.04E-02
	Upper middle class	7.29E-03	3.14E-04	-1.02E-02	6.38E-03	2.59E-02	5.93E-03	4.02E-04	-1.42E-02	5.35E-03	2.73E-02
	Upper class	5.31E-04	1.22E-04	-8.17E-04	9.33E-05	2.77E-03	5.44E-04	1.44E-04	-1.95E-03	1.73E-04	3.77E-03

NOTE: Based on the local-linear hedonic price regression with a Gaussian kernel for continuous variables and a Li-Racine kernel for discrete variables. Effects for make, year, quarter, and region fixed effects are not shown. For the continuous variables (PVFC, HPW, Weight), the statistics for both the gradient estimates of the hedonic price function with respect to the attributes ("Estimate") and their standard errors (SE) are shown.

Chapter 4

Metric and Scale Effects in Willingness-to-Pay for Environmental Benefits[1]

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Abstract

The present study investigates how the framing of information on the environmental impact of vehicles affects consumers' preferences for identical improvements in car quality. In online choice experiments, the effects of two metrics (fuel consumption vs. CO_2 emissions) and three scales of one metric (CO_2 in kg/km vs. g/km vs. g/100 km) are examined. First, from a technical perspective, fuel consumption (FC) and CO_2 emissions are linearly connected by a constant factor and are thus isomorphic in describing the environmental friendliness of a car. Second, rescaling identical information should not change consumer decisions. However, as this study demonstrates, the type of information presented to consumers significantly affects consumer valuation of environmental benefits from a reduction in FC or CO_2. The study's contribution lies in quantifying the differences in consumers' preferences for two measures of the same information that have not been previously directly compared. Additionally, the differences in the framing effects are explored for diesel and gasoline vehicles. The estimation accounts for heterogeneity in the tastes, environmental attitudes and knowledge of the respondents. The insights of this study serve to guide policy makers and car manufacturers on how to present information on car offers.

[1]Presented at the internal seminars; the 2017 Ph.D. Conference in Behavioural Science, UCD Geary Institute for Public Policy, Dublin, 30.11.2017; the 3[d] CRC-Workshop of the CRC Rationality and Competition, Berlin Schwanenwerder, 21.-23.03.2018; and the 40[th] Annual ISMS Marketing Science Conference, Temple University, Fox School of Business, Philadelphia, 13.-16.06.2018.

Keywords: Choice architecture; environmental impact; framing effects; vehicle choice
JEL Classification: D12, D90, M31, Q51.

4.1 Introduction

Information provision in the form of energy labels for energy-consuming durable goods is an instrument of government policy to reduce environmental pollution and address issues related to climate change. Road transport is the second-largest source of greenhouse gas (GHG) emissions in the European Union, and passenger vehicles account for 12% of total European Union emissions of carbon dioxide (CO_2), the main GHG that contributes to climate change.[2] To reduce transport CO_2 emissions, environmental policies (e.g., Directive 1999/94/EC in the EU[3] and 49 CFR 575.401 in the US[4]) ensure that information on the fuel efficiency and CO_2 emissions of passenger cars is made available to consumers to facilitate informed choices. As a demand-side policy, car labeling is a complementary measure to the specific CO_2 emission targets imposed on car manufacturers. For policies on both the demand and supply sides to be effective at promoting low-carbon and fuel-efficient vehicles, it is crucial that consumers value improvements in the fuel consumption (hereafter, FC) and CO_2 emissions of cars. From a technical perspective, these two metrics are linearly connected by a specific (constant) factor and thus are equivalent in describing the environmental impact of vehicles.[5] However, it remains unclear whether consumers value improvements in CO_2 as much as improvements in FC. If consumers' car choices vary across metrics, such shift in choices may lead to negative financial consequences for consumers and higher environmental costs from car use.

The aim of the current study is to investigate whether and how consumers differ in their preferences and willingness-to-pay (WTP) for identical improvements in the FC versus CO_2 emissions of cars. No prior work has directly compared consumers' preferences for these two metrics. Prior research on revealed preferences has not been able to separately identify these effects because the metrics are correlated, and research on stated preferences has focused either on one of these environmentally important attributes or simultaneously considered both measures. To separately

[2] https://ec.europa.eu/clima/policies/transport/vehicles/cars_en (accessed: March 08, 2018).
[3] http://eur-lex.europa.eu (accessed: March 08, 2018).
[4] https://www.ecfr.gov (accessed: March 08, 2018).
[5] One liter of fuel produces approximately 26.5 and 23.2 grams of CO_2 per kilometer driven by diesel and gasoline vehicles, respectively (http://www.kba.de/SharedDocs/Publikationen/DE/Statistik/Fahrzeuge/FZ/Fachartikel/emission_20110315.pdf, p. 6; accessed: March 08, 2018).

identify preferences for FC versus CO_2 emissions in this study, participants were presented with choice experiments that showed information either on FC or CO_2 emissions and were asked to choose a car to rent for an extensive holiday trip. As a result, the present study recovers the WTP for marginal changes in FC and CO_2 independently and, additionally, is able to quantify relative differences in these values for each person and relate them to individual-specific characteristics.

The current research relates to the broad literature on how choice architecture – how choices are presented, described, and structured – affects consumers' decisions (Tversky and Kahneman, 1981; Thaler et al., 2014; Münscher et al., 2016). In contrast to previous research, the current study does not examine the effect of valence framing of information (Levin et al., 1998; Avineri and Waygood, 2013) but explores the differences in consumers' WTP for environmental benefits when they are represented in terms of two metrics that have not previously been explicitly compared. The description of the environmental impact of car options in terms of FC and CO_2 represents a specific type of choice architecture (Ungemach et al., 2017). For a rational agent, the presentation of both attributes is redundant because each metric presents a "translation" of the same underlying information (Ungemach et al., 2017). However, prior research has demonstrated that consumers might perceive various measures of the same information differently (hereafter, a metric effect). For example, when the fuel efficiency of cars is framed in terms of fuel per distance (e.g., in l/100 km), instead of distance per unit of fuel (e.g., in km/l), people tend to have a more accurate perception of potential fuel savings (Schouten et al., 2014; Allcott, 2011; Larrick and Soll, 2008) – a perceptual error referred to in the literature as the "MPG illusion" (Larrick and Soll, 2008). As a result, this cognitive error may lead to suboptimal decisions at the consumer level and reduce demand for environmentally friendly vehicles. Camilleri and Larrick (2014) also observed that people tended to select a more fuel-efficient car when fuel economy was expressed as the fuel costs rather than the amount of fuel consumed.

In addition to the metric effect, prior work has also indicated that a change in the units in which quantitative information is provided affects consumer preferences (Pelham et al., 1994; Burson et al., 2009). The same attribute differences appear larger on scales with many units or expanded scales than on contracted scales (hereafter, a scale effect; Pandelaere et al., 2011). This effect was explained by people's tendency to judge quantitative information by the number of units without considering the type of the units. For example, Camilleri and Larrick (2014) found that information on fuel costs on the most expanded scale (as in 5,000 per 100,000 miles) resulted in higher preferences for a more fuel-efficient alternative than on other more contracted scales (as in 5 per 100 miles and 750 per 15,000 miles). Cadario et al. (2016) replicated the scale effect for information on carbon emissions

– consumers exposed to an expanded scale of CO_2 emissions (as in 100 g/km) more frequently selected an environmentally friendly car than those exposed to a contracted scale (as in 0.100 kg/km). The current paper extends the investigation of the scale effect in Cadario et al. (2016) by exploring the effects of three scales for CO_2 emissions (0.100 kg/km vs. 100 g/km vs. 10,000 g/100 km) that varied between subjects in the choice experiment. The use of three scales makes it possible to test for the default unit effect (Lembregts and Pandelaere, 2013) and a diminishing effect of scale expansion (Aribarg et al., 2017). The default unit effect would lead to higher WTP for an attribute expressed in familiar units (CO_2 in g/km in Germany and most European countries) compared to a more expanded scale (such as g/100 km), whereas the curvilinearity of the scale effect suggests that there is an inflection point at which the positive impact of scale expansion on attribute perception flattens and then reverses.

Compared to Cadario et al. (2016), Camilleri and Larrick (2014), and Pandelaere et al. (2011), the investigation in this paper is based on consumer choices from optimally designed choice experiments. Aribarg et al. (2017) also used optimal experiment designs, but that study focused only on the scale effect. Using a similar question as in Pandelaere et al. (2011) on perceived differences between two alternatives described by an attribute expressed on an expanded or a contracted scale, the current study found that participants were often inclined to opt for the middle response option regardless of the scale considered, potentially because they experienced difficulties in assessing the differences in the attribute values. Therefore, implementing an optimally designed choice experiment makes it possible to indirectly elicit consumer preferences for the investigated metrics by mimicking the actual choice situation, while additionally controlling for various determinants of choices.

Furthermore, the choice experiment in the present study is designed to be able to test for differences in the metric and scale effects by vehicle engine type (diesel versus gasoline). Because diesel and gasoline vehicles differ in both their environmental impact per unit of distance driven and fuel prices, consumers' perceptions of improvements in FC and CO_2 for these two types of vehicles may vary (Olson, 2013).

Various outcome measures are considered in the analysis: in addition to the proportion of choices in favor of a more environmentally friendly vehicle, attribute importance, and WTP for FC and CO_2 emissions, changes in individual choices between two alternatives that trade off on price per rental day, total financial costs, and total environmental costs are examined with respect to the framing of information (metric and scale effects). The distribution of the WTP for FC or

CO_2 emissions is recovered by estimating a mixed (random coefficient) logit model that accounts for consumers' unobserved heterogeneity in tastes in addition to the observed heterogeneity in the respondents' socio-demographic characteristics, car use experience, and environmental attitudes and knowledge.

The results of the present study suggest that participants value improvements in FC significantly more highly than the corresponding reduction in CO_2 emissions. Moreover, this discrepancy is greater when CO_2 emissions are presented on the most contracted scale. On the most contracted CO_2 scale (in kg/km), respondents are willing to pay, on average, for only 55% of the fuel savings and environmental benefits from better FC and CO_2 emissions. Individual attitudes and knowledge concerning environmental and climate issues significantly contribute to reducing the framing effects. There is a significant difference in consumers' choices based on whether they are driven by financial or pro-environmental motives. Based on this paper's findings, if consumers' car choices are guided solely by financial incentives, they may neglect the environmental damage caused by cars with lower fuel economy when information on CO_2 emissions, instead of FC, is presented.

Examining consumer valuations of and propensity to choose an environmentally friendly car is of great interest to policy makers. The insights from the current study are useful to understand how metric and scale design, as a choice architecture tool, can be used to "nudge" consumers to make better decisions (Thaler and Sunstein, 2008; Johnson et al., 2012). As the findings indicate, presenting information on the environmental impact of cars and policies that increase people's awareness of the correlation of FC and CO_2 emissions are both crucial to generate reductions in carbon emissions from vehicle use. Thus, this study also contributes to the literature on information-based policies for energy-consuming durable goods (Teisl et al., 2008; Newell and Siikamäki, 2014; Cohen and Vandenbergh, 2012; Heinzle, 2012) applied to vehicle preferences. Furthermore, the results may inform car manufacturers how to address the environmental benefits of car offers in their advertising (Xie and Kronrod, 2012; Chang et al., 2015).

The remainder of this paper proceeds as follows. Section 4.2 and Section 4.3 present the conceptual framework and research methodology, respectively. Section 4.4 describes the data and presents initial (model-free) evidence for the metric and scale effects on consumers' preferences for environmental benefits. Section 4.5 discusses the results of the estimation. Section 4.6 critically examines the findings, discusses the conceptual contributions and limitations of the study, and proposes future research directions. Section 4.7 concludes.

4.2 Conceptual Framework

The present research tests three main hypotheses. The first hypothesis (H1) is designed to replicate the results of previous studies on the scale effect (Pandelaere et al., 2011; Cadario et al., 2016; Camilleri and Larrick, 2014). The current study examines the effects of three scales for presenting information on CO_2 emissions – kg/km, g/km, and g/100 km. CO_2 values in kg/km correspond to the most contracted scale relative to those in g/km and g/100 km, whereas g/100 km is the most expanded scale. For example, 0.001 kg CO_2 per kilometer is equal to 1 g CO_2/km and 100 g CO_2/100 km. According to the scale effect, consumers should perceive same attribute differences to be larger when the attribute is expressed on expanded versus contracted scales, and thus, the WTP for improvements in CO_2 emissions should increase as the scale is expanded. Following the reasoning above, the first hypothesis suggests the following result:

H1a: WTP (100 g CO_2/100 km) > WTP (1 g CO_2/km)

H1b: WTP (1 g CO_2/km) > WTP (0.001 kg CO_2/km)

The three scales considered here also make it possible to investigate the potential curvilinear relationship between scale expansion and attribute importance weight (Aribarg et al., 2017) and to examine the role of the default unit effect (Lembregts and Pandelaere, 2013). The former effect would manifest in a diminishing positive impact of scale expansion on the WTP for improvements in CO_2 emissions (differences in WTP in H1a smaller than those in H1b). The default unit effect would result in a smaller WTP for CO_2 reduction when the attribute is expressed in g/100 km (despite its expanded scale) than in g/km (reverse H1a), as the latter unit is the default presentation of CO_2 emissions in Germany and many European countries.

The other two hypotheses are novel and concern the metric effect. First, consumers' WTP for identical improvements in cars' environmental-friendliness is hypothesized to be greater when information on FC, instead of CO_2 emissions, is presented (H2a and H2b):

H2a: Diesel ΔWTP = WTP (1 l/100 km) - WTP (26.5 g/km) > 0

H2b: Gasoline ΔWTP = WTP (1 l/100 km) - WTP (23.2 g/km) > 0

This hypothesis is based on the presumption that financial costs are more important for consumers than environmental costs. According to the theory of context-dependent choices, consumers may attach disproportionately large weights to salient attributes and be inattentive to less salient or obvious information (Bordalo et al., 2013; Gsottbauer and van den Bergh, 2011). In the context of automobile choice decisions, a car's price might be more important for consumers than its ongoing fuel costs, and fuel costs might be more salient than environmental costs.

Finally, the differences in consumers' perceptions of and WTP for the two metrics are explored across diesel and gasoline vehicles (H3). Because diesel fuel is less expensive, individuals may prefer diesel vehicles due solely to a financial motive, to save on operating costs. Accordingly, these consumers could more frequently pay attention to FC but not to CO_2 emissions than do drivers of gasoline vehicles. For example, in one of the conjoint studies that included the effects of pro-green attitudes on car choices, Olson (2013) found that, relative to gasoline buyers, diesel buyers have less interest in environmental issues and are more likely to seek the cheapest alternative regardless of its impact on the environment.

H3: Diesel ΔWTP > Gasoline ΔWTP

All hypotheses are formulated in terms of average effects. Additionally, individual differences may weaken or amplify the proposed relationships. For example, education and pro-environmental attitudes are expected to be associated with more accurate perceptions of the environmental impact of vehicles (Meyer, 2015; Poortinga et al., 2004; Hines et al., 1987) and thus result in smaller discrepancies in the WTP between the metrics and scales. Various consumer characteristics are included in the estimated models to study these differences.

4.3 Research Methodology

4.3.1 Questionnaire design

As a framework to study the effects of the framing of vehicles' environmental impact, this study considers a car rental for a holiday trip. In contrast to automobile purchases, the choice of which car to rent is less complicated because it features a lower degree of uncertainty regarding one's own car usage, entails no maintenance costs, depreciation (hence, there is no need to consider its resale value), or personal identification with the car (hence, a limited status effect), and allows the consumer to choose a suitable car for each specific occasion. Rental's lower financial investment relative to car purchase also provides this study with a larger pool of potential respondents. Because a longer trip with a rented car (e.g., a holiday trip) has non-negligible environmental and financial consequences, the choice of better fuel economy or lower CO_2 emissions may be important in the decision-making process for a car rental.

A questionnaire to study personal attitudes towards and preferences for selected features of a car rental service in Europe was developed with the aid of Sawtooth software (Lighthouse Studio Version 9.4.0). The questionnaire contained an introduction to the survey, which described its purpose, time required for completion, and an incentive to participate; questions regarding respondents' car rental experience; two choice experiments that were separated by questions on respondents' perceptions of differences between pairs of attribute levels in terms of their environmental benefits; questions on respondents' knowledge of and attitudes towards environmental issues and car use; and finally, questions on respondents' socio-economic characteristics. In addition to the respondents' car rental experience, prior to the choice experiments, participants were asked to indicate how important various characteristics of rental car offers are in their choice decisions. As Sanbonmatsu et al. (2003) showed, consideration of choice criteria prior to the evaluation can mitigate hypothetical bias in choice experiments.[6]

The environmental attitudes and knowledge of the respondents were measured with various scales. First, the scale used by the German Federal Environment Agency was used – the "General Environmental Consciousness" scale (UBA, 2016; Best, 2011). This scale combines cognitive, affective, and conative environmental orientations into a single score. Second, statements related to the perception of car use, financial motives, and knowledge were taken from previous studies or formulated specifically for the present study. Table 4.17 presents all statements used in the survey. The order of the items varied among the respondents. Responses were measured on a four-point Likert scale from "strongly disagree" to "strongly agree" and also included a "do not know" option. Additionally, the participants reported how well informed they are on issues related to climate change and how significant the problem of climate change is to them personally. These questions were presented to participants after the choice experiments to mitigate a priming of their decisions as being environmentally related.

Within the choice experiments, participants were asked to assume that they planned to rent a car for a ten-day holiday trip and to drive 2000 kilometers in total. Additionally, fuel prices for diesel and gasoline were provided. Respondents were asked to consider the presented car offers to be identical and acceptable to them in all attributes not mentioned and were informed that comprehensive insurance coverage and all rental fees were included in the price per day. Participants

[6] The literature provides mixed evidence on the presence and size of hypothetical bias in choice experiments (Hensher, 2010; Murphy et al., 2005; Carlsson and Martinsson, 2001; Ding, 2007).

responded to two choice experiments – with information either on FC (hereafter, the FC design) or CO_2 emissions on various scales (hereafter, the CO_2 design) as one of the attributes of the presented car options. The next subsection provides details on the development of the experiments.

4.3.2 Development of choice experiments

To explore the metric and scale effects on consumer preferences, four designs (FC + $CO_2 \times 3$ scales) of the choice experiment were developed. Each design had three attributes: engine type, with two levels; price per day, with four levels; and metric (FC or CO_2), with four levels (see Table 4.1). The attribute levels were selected to correspond to current market offers.

Table 4.1: Attributes and their levels in the choice experiments

(1)	(2)	(3) Metric			
Engine	€/Day	FC	CO_2		
		l/100 km	g/100 km	g/km	kg/km
Diesel	23	3.2	8,500	85	0.085
Gasoline	26	4.2	11,100	111	0.111
	30	5.2	13,800	138	0.138
	33	6.2	16,400	164	0.164

The metric (FC or CO_2) varied within subjects, whereas the CO_2 scale varied across subjects. The within-subject design enables this study to compare preferences for FC versus CO_2 for the same participants; the between-subject design makes it possible to eliminate learning effects while investigating the impact of various scales on choices. The order of the presentation of the choice tasks for either the FC design or CO_2 design, the position of the displayed attributes within choice tasks, and the order of profiles were randomized across participants.

Because each participant had to respond to two choice experiments, the number of choice tasks per experiment was restricted to be fewer than 20.[7] Based on the D-optimality criterion using the statistical software SAS (see the appendix for the design details), 14 choice tasks for each design were constructed. Each choice task consisted of two car alternatives and the no-choice option. Whereas the SAS procedure defined the first alternative, the second option was constructed manually

[7]According to Johnson and Orme (1996), having more than 20 choice tasks may lead to reduced data quality due to participants suffering cognitive overload.

to ensure that there are no dominated alternatives and there is an overlap among attribute levels within a task to be able to measure an interaction effect of engine type with the metrics. Moreover, the levels of the rental price were selected to ensure that there are alternatives within choice tasks that trade off on the price per day, total financial costs, and environmental costs. Total financial costs (TC) were computed as $\text{P} \times \text{Days} + \text{FC}/100 \times \text{FP} \times \text{KM}$, and the environmental costs (EnvC) were given by $CO_2 \times \text{KM}$, where P is the rental price in € per day, FC is fuel consumption in liters per 100 kilometers, FP is fuel price for diesel or gasoline in €/liter, CO_2 is the amount of CO_2 emissions in g/km, and KM stands for kilometers driven over 10 days. For example, if an alternative with the highest price per day in a choice task should have the lowest total financial costs, then the following condition should hold:

$$(P1 - P2) < (FP2 \times FC2 - FP1 \times FC1) \times \frac{KM}{Days \times 100}$$

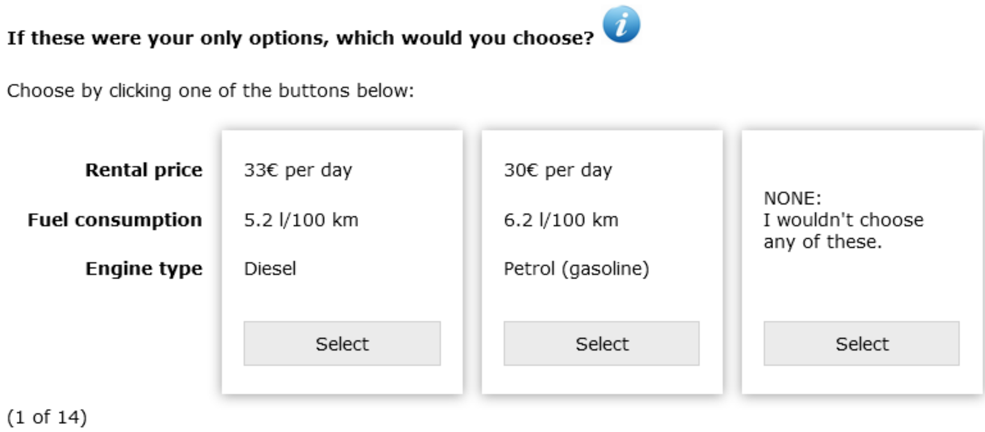
A similar condition was also satisfied for the CO_2 design. The D-efficiency of the final experimental design with 14 choice tasks, 3 alternatives, linear effects of the attributes, and restrictions on the composition of the second option is 93.81% (compared to an unrestricted version, created by the shifting method).

The examples of one choice task for the FC design and the CO_2 design are presented in Figure 4.1, where the first option has the lowest financial and environmental costs, while the second option has the lowest price per day. If respondents consider only price information, then suboptimal decisions are made. Tables 4.14 and 4.15 contain the total financial and environmental costs for each option in all choice tasks for both experimental designs. On average, these values across products in the experiments constitute €401 and 240 CO_2 kg, respectively.

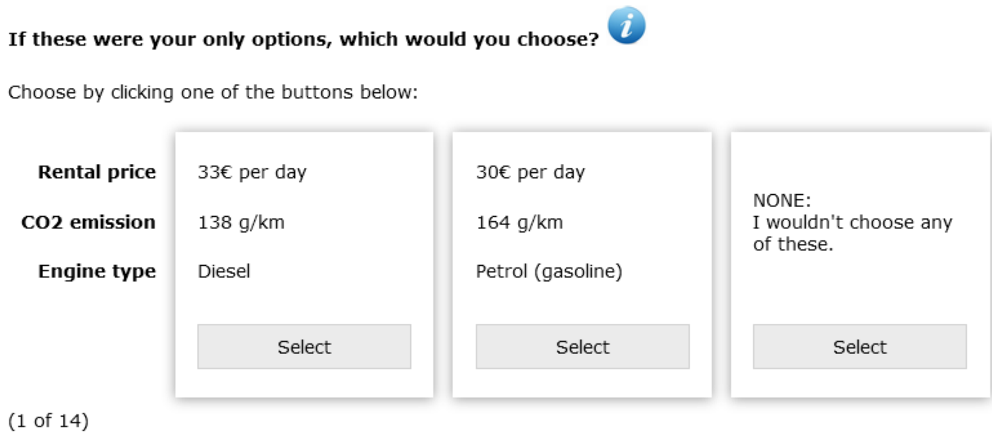
The experimental design was additionally tested on simulated choices, which were generated following the random utility theory (as discussed in the next section). The number of simulated respondents was varied to evaluate the statistical power in estimating the parameters, including the interaction term. A sample size of 400 or more individuals is sufficient to efficiently evaluate the effects of the proposed experimental designs (see Table 4.16 for the results).

Figure 4.1: Examples of one choice task for two experimental designs

(a) FC design



(b) CO_2 design



4.3.3 Model specification

The choices between options in the experiments are modeled according to random utility theory (McFadden, 1973; Train, 2009). It states that a rational economic consumer selects the option among a finite set of alternatives that provides the highest utility, with utility being a latent construct modeled in a probabilistic way. Individual choices related to characteristics of the persons and/or alternatives are used to infer their contributions to the utility derived from products. Following standard notations in the literature, the utility U_{njt} that consumer $n \in \{1, ..., N\}$ obtains from alternative $j \in \{1, ..., J\}$ for a choice situation $t \in \{1, ..., T\}$ consists of two additive components: a deterministic part V_{njt} and a non-observable random part ε_{njt} (Train, 2009; McFadden and Train, 2000). The deterministic part is assumed to be a linear-additive utility function of observed product attributes. The random part is given by ε_{jnt} and reflects unobserved determinants that influence consumer choices. Given the attributes in the current study, the utility function is specified as in Equation 4.1:

$$\begin{aligned} U_{njt} = V_{njt} + \varepsilon_{njt} = \alpha_{0n} \cdot \text{None}_{njt} + \alpha_{1n} \cdot \text{Engine}_{njt} - \alpha_{2n} \cdot \text{Metric}_{njt} \\ + \alpha_3 \cdot \left(\text{Metric}_{njt} \cdot \text{Engine}_{njt}\right) - \beta_n \cdot P_{njt} + \varepsilon_{njt}, \end{aligned} \tag{4.1}$$

where None_{njt} is the no-choice option, the utility of which is given by $U_{0nt} = \alpha_{0n} + \varepsilon_{0nt}$; P_{njt} indicates the rental price in €/day; Engine_{njt} stands for engine type (diesel vs. gasoline); Metric_{njt} represents either FC in l/100 km or CO_2 in g/km; α_n are the utility coefficients that reflect the associated importance weights assigned by consumers to each of the product attributes except price; and β_n is the price sensitivity. The unobserved term ε_{njt} is assumed to be *iid* extreme value. While α_3 is fixed for all individuals, the taste parameters α_{0n}, α_{1n}, $\ln(\alpha_{2n})$, and $\ln(\beta_n)$ are allowed to vary across individuals and are assumed to be multivariate normally distributed, with $\bar{\theta}$ being a vector of population means of the parameters and Σ being a variance-covariance matrix:

$$\theta_n = [\alpha_{0n}, \alpha_{1n}, \ln(\alpha_{2n}), \ln(\beta_n)]' \sim MVN(\bar{\theta}, \Sigma)$$

Engine type enters the utility function with a normally distributed coefficient because different people might prefer different fuels. The coefficient on the interaction term reflects differences in consumers' perceptions of improvements in the metric for diesel and gasoline vehicles and can take either signs. The coefficients for the price β_n and the metric α_{2n} are restricted to be non-positive for all individuals by assuming log-normal distributions for these parameters. The mean of the metric coefficient is also allowed to depend on the observed respondents' characteristics as presented in Equation 4.2, where $\bar{\alpha}_2$ is the mean of the metric effect in the population, Z_{nk} is kth person-specific characteristic, π_k is its effect on the metric parameter, and $\sum_{m=1}^{4} \sigma_{2m}\eta_{2n}$ is a linear combination of $\eta_{2n} \sim N(0,1)$ and elements of a lower triangular (Cholesky) matrix σ_{2m} for all random utility parameters. The coefficient of the interaction term of engine type and metric is held constant across individuals.

$$\alpha_{2n} = \bar{\alpha}_2 + \sum_{k=1}^{K} \pi_k \cdot Z_{nk} + \sum_{m=1}^{4} \sigma_{2m}\eta_{2n} \tag{4.2}$$

The specified random coefficient or mixed logit (hereafter, MXL) model yields the probability that decision-maker n will choose a specific sequence of alternatives $\mathbf{j} = \{j_1, ..., j_{Tn}\}$, which is given by the integral of the standard logit formula over the density of θ_n parameters (Equation 4.3).

$$MXLP_{nj} = \int_{-\infty}^{\infty} \prod_{t=1}^{T_n} \left(\frac{\exp(V_{njt})}{\sum_l \exp(V_{nlt})} \right) f(\theta) d\theta \tag{4.3}$$

The parameters in Equation 4.3 remain constant within decision-makers, but vary across persons. To estimate the parameters of the density distribution of θ_n, the present study uses a Maximum Simulated Likelihood approach (Train, 2009; Bhat, 2001), whereby 2000 Halton draws are employed to approximate the log-likelihood function[8].

To ease the interpretation of the estimation results, measures of relative attribute importance (RAI) weights and WTP for two metrics are used. The RAI equals the relative range in the utility estimates for an attribute, computed for each person (Verlegh et al., 2002). The WTP for an improvement in FC or CO2 is given by the negative of the ratio of the coefficients for the metric and price (Train, 2009):

$$WTP_n = -\frac{\alpha_{2n} + \alpha_3 \times \text{Engine}}{\beta_n}$$

[8] Train (2009) argues that Halton draws provide better approximations to the integral than (pseudo-) random draws. In the case of many explanatory variables, a number of draws greater than 1000 is recommended to reduce a simulation noise (Elshiewy et al., 2017b). See also Elshiewy et al. (2017a) for an overview of implementation of the discrete choice models.

All derived measures (RAI, WTP, shares) are computed from 10,000 draws from the estimated population distribution of the taste parameters. Additionally, to reflect the estimation error, standard errors and confidence intervals for all measures are evaluated by using 300 bootstrap samples of the draws (Efron and Tibshirani, 1986).

Because of the interdependence between the FC and CO_2 values, the WTP for one of these environmentally important car characteristics implies the WTP values for the other metric. For example, the implied WTP (FC) values based on the estimated WTP (CO_2) can be computed as WTP (CO_2)$\times$24.85 for both engine types on average. The reciprocal functional relationship holds for the implied WTP (CO_2) based on the estimated WTP for fuel consumption.

4.4 Data and Initial Insights

This section describes the data and presents initial (model-free) evidence for metric and scale effects on consumers' preferences for environmental benefits.

4.4.1 Summary statistics

This study uses a convenience sample. Participants were recruited online from July to November 2017 via social media networks, networks of students from German universities, and various online platforms to collect data (e.g., PollPool, SurveyCircle). Respondents were incentivized by the chance to win one of 10×20-euro Amazon gift cards. The questionnaire was offered in either English or German. Only individuals who were 18 years of age or older were eligible to complete the survey. Of the 759 participants in the survey, 173 were excluded from the sample because they 1) completed the survey within less than five minutes[9] or 2) had a specific response pattern in the choice-based conjoint experiments (e.g., always selected the same of three options).

The final sample of 586 respondents is equally distributed across the various designs. No statistically significant differences in the respondents' socio-demographic characteristics (e.g., gender, age, income) or car rental experience were found across the designs (see Table 4.2). On average, it took 16 minutes for the participants to complete the questionnaire. The sample consists predominantly of participants from Germany, with an average age of 29 years, of both genders in similar proportion,

[9] Five minutes was the least amount of time needed to complete the questionnaire.

and an average net monthly income of €1,000 – €1,500. More than 60% of the participants have experience with a car rental service, and more than 80% of them had rented a car within the previous two years. Those participants who had rented a car for a holiday or tourism (approximately 80% of the sample) had driven, on average, 151 kilometers over nine days. Hence, the proposed scenario for the choice experiment is consistent with real-world experiences of car rentals for holiday trips.

Several variables related to the respondents' environmental attitudes and knowledge were also measured. Table 4.18 presents an overview of participants' responses to these variables. The scale for the responses varied from 1 ("strongly disagree") to 4 ("strongly agree") and also included a "do not know" option. Applying confirmatory factor analysis, the first nine items were combined into a single score for the "General Environmental Consciousness" (GEC) scale (UBA, 2016; Best, 2011). The Cronbach's α for this scale is 0.83 with a bootstrap confidence interval of 0.80-0.86.[10] The path diagram and model fit statistics are presented in Figure 4.3. Other items served as potential covariates in the discrete choice models to control for the observed heterogeneity related to the perception of car use, financial motives, and knowledge. For example, a majority of the respondents (72%) reported being willing to pay higher prices for products that pollute less. On the other hand, for 61% of respondents, improvements in a car's FC were foremost linked to financial savings. Moreover, only 12% of the respondents were aware of the link between values of FC and CO_2 emissions.

In the choice experiments, the average share of the no-choice option did not exceed 5% for both designs. This implies that respondents more often substituted between the two car options and did not exit the market in response to choice set compositions. The average choice shares for the first and second alternatives were 51.3% and 44.19% in the FC design and 46.42% and 48.76% in the CO_2 design, respectively.

4.4.2 Model-free evidence

Similar to Pandelaere et al. (2011) and Aribarg et al. (2017), respondents were asked to indicate their perceptions of differences between two values of one attribute (FC or CO_2). In the FC design, the question was *"In your perception, how much is a car with FC of 5.2 l/100 km ecologically better than a car with 6.2 l/100 km?"*, with seven possible responses ranging from 1 ("Not at all") to 7 ("Extremely"). For the CO_2 design, similar questions with two pairs of the corresponding values

[10] The bootstrap confidence interval was computed based on 1,000 bootstrap samples of size 400 from the initial 586 observations.

Table 4.2: Summary statistics of the sample by experimental design

Characterisitcs	Units	CO_2 in g/100 km (N = 194) Mean	SD	CO_2 in g/km (N = 196) Mean	SD	CO_2 in kg/km (N = 196) Mean	SD	Total Sample (N = 586) Mean	SD
First shown (FC Design=1)	0/1	0.53	0.50	0.48	0.50	0.47	0.50	0.49	0.50
Time spent	minutes	17.82	13.30	15.64	10.93	13.61	8.59	15.69	11.22
Country of residence (Germany=1)	0/1	0.98	0.15	0.97	0.17	0.93	0.25	0.96	0.19
Gender (Male=1)	0/1	0.46	0.50	0.47	0.50	0.49	0.50	0.47	0.50
Age	years old	28.37	10.36	28.84	9.76	28.68	9.93	28.63	10.00
Net monthly income	group	2.67	1.68	3.11	1.79	3.14	1.81	2.97	1.77
Children under 18 (Yes=1)	0/1	0.12	0.33	0.16	0.37	0.10	0.30	0.13	0.33
University degree (Yes=1)	0/1	0.51	0.50	0.59	0.49	0.62	0.49	0.57	0.50
Own car (Yes=1)	0/1	0.36	0.48	0.35	0.48	0.37	0.48	0.36	0.48
Rental experience (Yes=1)	0/1	0.64	0.48	0.63	0.48	0.62	0.49	0.63	0.48
Rented 1+ time over the past 2 years (Yes = 1)	0/1	0.87	0.34	0.85	0.36	0.85	0.36	0.86	0.35
Holidays/tourism (Yes=1)	0/1	0.77	0.42	0.76	0.43	0.84	0.37	0.79	0.41
N days (holidays)	number	8.97	10.71	8.13	5.71	8.77	6.95	8.63	8.03
Km per Day (holidays)	kilometers	145.22	103.94	163.82	153.71	144.27	126.73	150.93	129.64

NOTE: The average monthly income was computed without responses for income group 8 ("Prefer not to answer") and corresponds to "€1,000 to under €1,500" (group 3). There are no statistically significant differences in the respondents' socio-demographic characteristics or car rental experience across the designs.

for CO_2 emissions were offered, which varied with the scale and engine type. For example, a car with a FC of 5.2 l/km emits 138 grams of CO_2 per kilometer (0.138 kg/km or 13,780 g/100 km) in the case of a diesel engine and 121 g CO_2/km (0.121 kg/km or 12,064 g/100 km) in the case of a gasoline engine. For all pairs, the first option is 16% ecologically better. Table 4.3 presents average values for all pairs of the comparison and the confidence interval for the perceived differences. The results are in line with the prediction that a more expanded scale induces greater perceived differences in the values of attribute levels. Thus, the scale effect occurs due to a shift in mental representations of attribute values. Additionally, differences in the attribute levels are perceived to be larger for diesel cars than for gasoline cars. However, statistically significant differences in the responses are observed only among values for FC versus CO_2 in kg/km and CO_2 in g/100 km (the most expanded scale) versus CO_2 in kg/km (the most contracted scale). The respondents tended to select a middle response option, probably due to the difficulty they had in comparing cars' performance on these values. Therefore, it is essential to also indirectly elicit the metric and scale effects on consumer decisions, for example through choice experiments.

Table 4.3: Pairs of attribute values to compare and their evaluations

Design	Engine[a]	Option 1	Option 2	N	Mean	SE	90%-CI
FC (l/100 km)	Diesel & Gasoline	5.2	6.2	563	4.50	0.05	(4.41; 4.58)
CO_2 (g/100 km)	Diesel	13,780	16,430	189	4.63	0.09	(4.48; 4.78)
	Gasoline	12,064	14,384	189	4.23	0.09	(4.08; 4.38)
CO_2 (g/km)	Diesel	138	164	182	4.42	0.10	(4.26; 4.58)
	Gasoline	121	144	182	4.23	0.10	(4.07; 4.39)
CO_2 (kg/km)	Diesel	0.138	0.164	180	4.26	0.10	(4.09; 4.42)
	Gasoline	0.121	0.144	180	4.09	0.10	(3.92; 4.25)

NOTE: Responses to the question *"In your perception, how much is [Option 1] ecologically better than [Option 2]?"* The response scale had seven options ranging from 1 ("Not at all") to 7 ("Extremely"). (a) Respondents did not receive the information on the engine type.

As the next step, the data from the choice experiments are analyzed, and model-free evidence of the metric and scale effects is presented. First, the choice shares of attribute levels for FC versus CO_2 (see Table 4.1) are compared across designs. Table 4.4 demonstrates that respondents selected the highest attribute level that corresponds to higher fuel costs and environmental costs more often 1) under the CO_2 design than under the FC design (H1 supported) and 2) under the more contracted CO_2 scale (H2 supported). The first finding suggests that the two metrics are perceived differently, despite their correlation, and the second finding implies that the shift in the mental representation of attribute values due to the scale effect leads to different choices for the same person.

Table 4.4: Choice shares of attribute levels by design (in %)

Design	Level 1 (the lowest)	Level 2	Level 3	Level 4 (the highest)
FC (l/100 km)	36.99	23.14	18.89	16.45
CO_2 (g/100 km)	30.50	23.54	17.50	22.94
CO_2 (g/km)	30.15	23.13	17.43	24.53
CO_2 (kg/km)	26.86	20.89	19.36	28.74

NOTE: Differences in the choice shares of attribute levels among the designs are statistically significant ($\chi^2 = 38.41$; $p<0.001$). Shares for the no-choice option are omitted.

Second, differences in the choices between two vehicles that trade off on rental price per day and environmental friendliness (in terms of FC or CO_2) for identical choice sets of various designs are examined. For example, in choice set 14, one alternative has the lowest rental price per day, while the other option has the lowest total financial costs (in euros for the ten days) and the lowest environmental costs (in kg of CO_2 over the ten days). Both alternatives also have the same engine type to control for preferences for diesel over gasoline cars. Because differences in the total financial and environmental costs between these two car options are identical in all experimental designs, there should be no differences in the choice shares due to the metric and scale used to present the information. Table 4.5 describes the choice task and demonstrates how the choice shares of the two alternatives change across designs. The results indicate that under a more contracted CO_2 scale, the appeal of the environmentally friendly option (EFO) decreases, and respondents' focus shifts towards the option with the lowest rental price. As a consequence, more respondents make suboptimal choices in terms of both personal financial costs and social environmental costs. In this choice task, the alternative with the lowest total financial costs also has the lowest environmental costs. Therefore, a high choice share for the environmentally friendly alternative under the FC design can be explained by consumers minimizing both of these costs. However, a sharp decline in the choice share in the CO_2 design suggests that the participants place greater weight on financial costs than on the environmental impact of the chosen vehicles. To better understand these preferences and the potential for preference reversal from the framing of information, the following section presents the findings from the discrete choice model estimation.

Table 4.5: Comparison of choices for an identical choice task (Task 14) over designs

	(1) Minimum-Price Option				(2) Environmentally Friendly Option				$\triangle TC^b$	$\triangle EnvC^c$
	Engine	€/day	Metric	Share[a]	Engine	€/day	Metric	Share[a]	(€)	(CO_2 kg)
FC (l/100 km)	Diesel	30	6.2	0.16 (0.02)	Diesel	33	4.2	0.73 (0.02)	14.00	106.00
CO_2 (g/100 km)	Diesel	30	16,400	0.41 (0.04)	Diesel	33	11,100	0.49 (0.04)	14.00	106.00
CO_2 (g/km)	Diesel	30	164	0.41 (0.04)	Diesel	33	111	0.45 (0.04)	14.00	106.00
CO_2 (kg/km)	Diesel	30	0.164	0.52 (0.04)	Diesel	33	0.111	0.38 (0.04)	14.00	106.00

NOTE: (a) Mean choice shares with standard errors in parentheses. (b) Differences in the total financial costs are $\Delta TC = TC_1 - TC_2 = (€/Day_1 - €/Day_2) \times Days - (FC_2 - FC_1) \times FP \times KM$. (c) Differences in the environmental costs are $\Delta EnvC = EnvC_1 - EnvC_2 = (CO_{2\,1} - CO_{2\,2}) \times KM$.

4.5 Estimation Results

4.5.1 Model fit

To econometrically explore the metric and scale effects on consumer preferences, discrete choice models are estimated under different model assumptions. First, the standard multinomial logit (MNL) models are estimated as a benchmark for comparing more complex models. Tables 4.22 and 4.23 present the parameter estimates from models based on data for the FC design and CO_2 design, respectively. The first column in both tables corresponds to the MNL models that do not include the respondents' observed heterogeneity. The other columns show how the parameter estimates for product attributes change after controlling for various sets of individual-specific variables. The last column in each table shows the results of the best fitted MNL model that serves to determine what individual-specific covariates to include in the MXL models.[11] The variables that capture observed heterogeneity enter the models via their interaction with the metric. Because income may directly affect consumers' price sensitivity, additional interaction terms between the rental price and dummy variables that identify respondents with below- or above-average monthly net income are included. All individual-specific variables (except for the two income dummies) are mean-centered prior to estimation.

Overall, the MNL parameter estimates are in line with expectations. The effects of price and metric (FC or CO_2) on choices are negative and statistically significant.[12] There is no significant effect of respondents' preferences for diesel versus gasoline engines. The interaction term between the metric and engine type is also statistically insignificant in both designs. As a result, the hypothesis on the differential metric effect for cars with different engine types (H3) is not supported. Hence, in the following models, the interaction term is not considered. The results from the model that includes an interaction between price and CO_2 scale reveals that the more contracted the CO_2 scale is, the more price sensitive respondents become. The corresponding price elasticity values indicate that a 1% price increase results in a 1.22% decrease in choice share for the FC design and a 1.73%, 1.99%, and 2.10% decrease for the CO_2 design with CO_2 measured in g/100 km, g/km, and kg/km, respectively.[13]

[11] For an explanation of how the variables were constructed, please refer to the appendix.

[12] Additionally, MNL models with the price and the metrics entering as separate dummy variables for each attribute level were estimated. No curvilinear effects in the price or metric coefficients were found. These estimation results are available upon request.

[13] The elasticity values are computed for the MNL model without individual-specific covariates.

In addition to the observed individual heterogeneity, unobserved consumer heterogeneity in tastes is accounted for by estimating MXL for both designs, as described in Section 4.3.3. The price and metric effects are specified to be log-normally distributed since every respondent is likely to prefer a lower level of these attributes, whereas taste parameters for other characteristics are normally distributed. In the MXL estimation, the maximum simulated likelihood method with 2000 Halton draws was used in all specifications. A likelihood ratio test rejects the standard logit specification (MNL1) relative to the mixed logit specification (MXL1) for both designs (FC design: $\chi^2(4) = 2178.7$, $p < 0.001$; CO_2 design: $\chi^2(4) = 3288.9$, $p < 0.001$). Furthermore, a mixed logit specification with correlated utility coefficients and correlation over choice situations results in a significant improvement in the model fit compared to the MXL that does not account for such correlation (Table 4.6). In the remainder of the paper, the focus is on the best fitting model, MXL3 (the estimation results are in Table 4.24) – the model that allows for all sources of correlation in tastes, including scale heterogeneity (Hess and Train, 2017). The estimated standard deviations of many of the coefficients are significant, which implies a substantial heterogeneity in the preferences for the attributes, even after controlling for the observed consumer characteristics. The estimated correlation among the taste parameters (Table 4.25) indicates moderate to strong associations among the tastes for product attributes. For example, the respondents who prefer diesel cars are also more price-sensitive and have higher utility from better (lower) FC or CO_2 values.

Table 4.6: Choice model fit comparison

	MNL1	MNL2	MXL1	MXL2	MXL3
	FC design				
log-Likelihood	-6021.34	-5437.49	-4932.01	-4756.84	-4244.40
AIC	12050.68	10908.97	9880.02	9541.68	8538.80
McFadden R^2	0.105	0.191	0.267	0.293	0.369
number of parameters	4	17	8	14	25
obs. heterogeneity	No	**Yes**	No	No	**Yes**
unobs. heterogeneity	No	No	**Yes**	**Yes**	**Yes**
taste correlation	No	No	No	**Yes**	**Yes**
	CO_2 design				
log-Likelihood	-6463.056	-5770.40	-4817.16	-4571.59	-4192.69
AIC	12942.11	11582.80	9658.32	9179.18	8443.38
McFadden R^2	0.023	0.128	0.272	0.309	0.366
number of parameters	8	21	12	18	29
obs. heterogeneity	No	**Yes**	No	No	**Yes**
unobs. heterogeneity	No	No	**Yes**	**Yes**	**Yes**
taste correlation	No	No	No	**Yes**	**Yes**

4.5.2 Attributes' importance weights and WTP

In the following, the metric and scale effects are discussed based on the relative attribute importance (RAI) and WTP values derived from the MXL parameter estimates. Summary statistics for the RAI and WTP are given in Table 4.7 and Table 4.8, respectively. The previously reported model-free findings for the metric and scale effects are confirmed. The highest importance of the rental price and the lowest importance of an environmentally related attribute are observed for the CO_2 design with the most contracted scale (kg/km).

The participants are willing to pay substantially more for improvements in the FC of vehicles than for a comparable reduction in CO_2 emissions (H1 supported), and the discrepancy between these values increases as the CO_2 scale contracts (H2 supported). The median WTP for a reduction in FC by one l/100 km is estimated to be €45 under the FC design, while the values for the same improvement based on the CO_2 design do not exceed €24 on average. According to the choice scenario, one less liter of fuel per 100 kilometers would result in saving 20 liters of fuel over ten days and 2000 kilometers or fuel savings of €24 for both engine types, on average.[14] Hence, the estimated WTP values suggest an overvaluation of fuel savings under the FC design and an almost exact or undervaluation of fuel savings under the CO_2 design, depending on the CO_2 scale. Concerning environmental costs, a 20-liter fuel reduction would reduce emissions by 50 kilograms of CO_2 for both engine types, on average. The assumed fuel prices also imply prices for CO_2. In the given scenario, one kilogram of CO_2 emitted by diesel and gasoline vehicles costs €0.42 and €0.56, respectively. The estimated WTP for reducing CO_2 by one g/km yielded €0.48, €0.35, and €0.27 per one kilogram of CO_2 for the three investigated CO_2 scales, ranging from the most expanded (g/100 km) to the most contracted (kg/km), respectively.[15] Therefore, the more contracted the CO_2 scale is, the more likely respondents are to undervalue the environmental costs (after also accounting for the estimation errors).

The estimated median WTP for the product category, or the costs at which a consumer is indifferent between purchasing and not purchasing a product (computed as in Gensler et al., 2012) lies between €466 and €671 across the products in the

[14] In the choice scenarios, respondents were informed that fuel prices are €1.10 and €1.30 for a liter of diesel and gasoline, respectively.

[15] These values are computed by dividing the median WTP (1 g/km) from Table 4.8 by 2000 kilometers and converting them into euro values per kilogram of CO_2.

Table 4.7: Relative attribute importance (MXL model)

Design \ Attribute	Price		Engine		FC or CO_2	
	Median	SE	Median	SE	Median	SE
FC (l/100 km)	0.34	0.02	0.15	0.01	0.46	0.01
CO_2 (g/100 km)	0.42	0.02	0.19	0.01	0.31	0.02
CO_2 (g/km)	0.48	0.02	0.19	0.01	0.26	0.02
CO_2 (kg/km)	0.51	0.02	0.20	0.01	0.21	0.02

NOTE: The table reports the median RAI values for an average sample person computed based on draws from the population distribution of the taste parameters. Standard errors are computed from 300 bootstrap resamples of the taste parameter draws.

Table 4.8: WTP (€) for FC and CO_2 over the whole trip (MXL model)

Design \ Attribute	FC (1 l/100 km)					CO_2 (1 g/km)				
	Median	SE	2.5%	97.5%	SD	Median	SE	2.5%	97.5%	SD
FC (l/100 km)	**-45.11**	**3.83**	**-52.87**	**-37.91**	**71.06**	-1.80	0.15	-2.11	-1.52	2.84
CO2 (g/100 km)	-23.90	2.24	-28.75	-20.22	92.91	**-0.96**	**0.09**	**-1.15**	**-0.81**	**3.72**
CO2 (g/km)	-17.44	1.54	-20.54	-14.69	67.63	**-0.70**	**0.06**	**-0.82**	**-0.59**	**2.71**
CO2 (kg/km)	-13.42	1.40	-16.14	-10.99	51.96	**-0.54**	**0.06**	**-0.65**	**-0.44**	**2.08**

NOTE: The table reports the summary statistics for WTP values in € for the whole trip (10 days; 2000 km) for an average sample person based on 10,000 draws from the population distribution of the taste parameters. Standard errors (SE) and confidence interval (2.5% and 97.5%) of the median are computed from 300 bootstrap resamples of the draws. SD stands for standard deviation. **Bold values**: computed from the estimates. Non-bold values: implied by the values from other designs. The implied WTP (FC) values based on the WTP (CO_2) are computed as WTP(CO_2)×25 for both engine types on average. The implied WTP (CO_2) values based on the WTP (FC) are computed as WTP(FC)/25 for both engine types on average.

experiment.[16] These values are on average 1.5 higher than the total financial costs of these products, but do not exceed the implied costs more than 2.2 times. Hence, first, the budget constraint for the participants in the survey is non-binding, and the estimated WTP for the metrics reflects consumers' preferences and not their financial inability to invest in a preferred car quality; second, the fact that the WTP values are close to the implied costs suggests an adequate choice setting for the experiment.

Individual differences in WTP. There is substantial variation in the WTP for FC and CO_2 in the population, as the standard deviation (SD) values in Table 4.8 suggest. Many individual-specific variables help to explain this variation. Table 4.9 reports the average differences in WTP for a one-unit improvement in each metric for individuals described by various observed characteristics. For example, the individuals who have an above-average GEC score also have higher WTP for both metrics. However, the difference in WTP for environmentally conscious consumers is significantly lower for the FC improvements than for the corresponding CO_2 reduction. While men are willing to invest in improvements of FC, they are reluctant to pay for improvements in CO_2. This finding indicates that respondents perceive identical improvements in these two metrics from different perspectives – reductions in FC are mainly linked to financial savings, whereas improvements in CO_2 are primarily related to the environmental impact of cars. The respondents fail to understand the correlation between these two measures.

On average, consumers value improvements in FC €28 more than a comparable reduction in CO_2 emissions. To understand the role of the observed consumer heterogeneity in the magnitude of the metric effect, differences in WTP between FC and CO_2 for various specific sub-groups in the population are further analyzed. While men without rental experience, with low GES scores, and who are unaware of the correlation between FC and CO_2 values have the highest metric effect (€36), the smallest difference in the WTP for the two metrics is observed for women with rental experience, high GEC scores, and awareness of the correlation between FC and CO_2 (€9). On average, the metric effect for environmentally conscious individuals is €26 and decreases with their knowledge of the correlation between FC and CO_2 (€18). Moreover, if environmentally conscious individuals perceive improvements in the FC of a car to represent more than just savings in financial costs, the metric effect decreases further to €12. Thus, a better understanding of the environmental impact of vehicles decreases the differences in the WTP for

[16]The median WTP for the product category is computed for each presented product based on the estimates of the FC design. The WTP values for the CO2 design have a greater overlap with the implied total financial costs of the products in the experiment.

the two metrics. Table 4.26 contains further results on population sub-groups of interest.

Table 4.9: Differences in WTP (€) for a reduction in FC and CO_2 by individual-specific variables

	△WTP, 1 l/100 km (FC design)		△WTP, 1 g/km (CO_2 design)	
	Mean	SE	Mean	SE
Gender (male = 1)	3.68	1.54	-0.01	0.11
University degree (yes = 1)	-1.41	1.44	-0.80	0.15
Rental Experience (yes = 1)	-5.45	1.88	-0.59	0.16
Environmental consciousness (score)	2.10	0.70	0.61	0.11
"WTP for less pollution" (yes = 1)	4.40	2.17	2.99	0.45
"Financial motive" (yes = 1)	-0.08	1.57	-0.65	0.18
"Diesel perception" (yes = 1)	0.47	1.97	0.23	0.14
"FC-CO_2 knowledge" (yes = 1)	-0.57	2.41	0.88	0.23

NOTE: The table presents the differences in WTP in € for FC and CO_2 for the whole trip (10 days; 2000 km) among respondents described by various characteristics. Values are computed based on 300 bootstrap resamples of draws for 10,000 random individuals from the estimated distribution of the taste parameters. Positive values mean higher WTP for a reduction in FC by 1 l/100 km or CO_2 emissions by 1 g/km compared to a reference group.

4.5.3 Market simulation

A market simulation can assist in exploring how choice shares among alternatives that trade off on the rental price per day, total financial costs, and environmental costs vary across the metrics and scales. The simulated data include all possible choice sets of two car options that are described by a rental price per day ranging from €23 to €33 by €1; FC ranging from 3.0 l/100 km to 6.2 l/100 km by 0.2 l/100 km; and two engine types (diesel and gasoline). These values were employed to compute the CO_2 emissions, total financial costs, and environmental costs for both car options in the choice tasks. All simulated choice sets also include the no-choice option. From all possible combinations of the selected car attributes, three types of choice sets for the market simulation are considered: (1) the choice sets in which one car has the minimum rental price, but the other option has the minimum total financial and environmental costs (10,698 sets); (2) the choice sets in which one car has the minimum rental price and the lowest total financial costs, but the other option has the lowest environmental costs (20,142 sets); and (3) the choice sets in which one car has the minimum rental price and the lowest environmental costs, but the other option has the lowest financial costs (1,195 sets). These three cases allow for an evaluation of the interplay of financial and environmental motives in consumers' decison-making.

Table 4.10 describes how two options differ in their financial and environmental characteristics in each case. In all cases, there are choice sets with a substantial trade-off between total financial and environmental costs. In the subsequent discussion, the focus is on the EFO, i.e., the option with the minimum environmental costs over the whole trip. In the first case, this option also minimizes the total financial costs, while in the other two cases, it is not financially optimal.

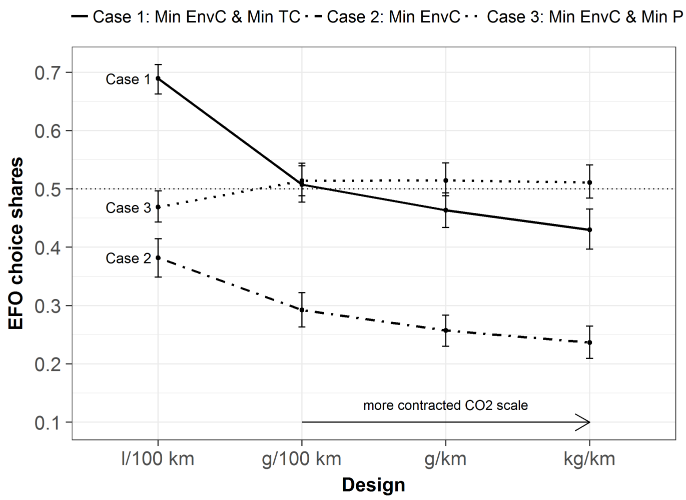
Table 4.10: Characteristics of the simulated choice sets

	Mean	Minimum	25%	Median	75%	Maximum
	Case 1 (N sets = 10,698) Option 1: Min P vs. Option 2: Min EnvC & Min TC					
△P (€)	-2.38	-9.00	-3.00	-2.00	-1.00	-1.00
△FC (l/100 km)	1.75	0.40	1.20	1.80	2.20	3.20
△CO_2 (g/km)	39.87	0.06	23.20	37.84	55.68	94.70
△TC (€)	22.77	0.00	8.40	19.60	33.20	85.20
△EnvC (CO_2 kg)	79.75	0.12	46.40	75.68	111.36	189.40
△EnvC (€)	32.28	0.06	22.27	36.33	53.45	90.91
	Case 2 (N sets = 20,142) Option 1: Min P & Min TC vs. Option 2: Min EnvC					
△P (€)	-4.86	-10.00	-7.00	-5.00	-3.00	-1.00
△FC (l/100 km)	0.78	-0.60	0.20	0.60	1.20	3.20
△CO_2 (g/km)	25.22	0.06	10.60	21.20	37.10	94.70
△TC (€)	-37.12	-138.00	-53.60	-32.80	-15.60	0.00
△EnvC (CO_2 kg)	50.44	0.12	21.20	42.40	74.20	189.40
△EnvC (€)	24.21	0.06	10.18	20.35	35.62	90.91
	Case 3 (N sets = 1,195) Option 1: Min EnvC & Min P vs. Option 2: Min TC					
△P (€)	-1.47	-3.00	-2.00	-1.00	-1.00	-1.00
△FC (l/100 km)	0.21	-0.40	0.00	0.20	0.40	0.60
△CO_2 (g/km)	-11.05	-29.74	-16.50	-9.86	-4.56	-0.60
△TC (€)	9.98	0.00	4.00	8.40	14.80	28.00
△EnvC (CO_2 kg)	-22.11	-59.48	-33.00	-19.72	-9.12	-1.20
△EnvC (€)	-10.61	-28.55	-15.84	-9.47	-4.38	-0.58

NOTE: △P, △FC, △CO_2, △TC, and △EnvC refer to the differences in rental price per day, FC, CO_2 emissions, total financial coats, and total environmental costs between the first and the second options in the simulated choice sets. Total financial and environmental costs are computed for the whole trip (10 days, 2000 kilometers). △EnvC (€) refers to the monetary values of the environmental costs computed for both engines on average based on the assumed fuel prices in the choice scenario (a diesel price of €1.10/liter and gasoline price of €1.30/liter). The values for the mean, the first and the third quartiles, the median, the minimum, and the maximum are given for each case of the simulated choice sets.

Figure 4.2 displays how the average choice share of the EFO changes depending on the experimental design and characteristics of the choice sets.[17] Although in case 1, the EFO is the cost-minimizing option, its share on average is less than a 100% and is lower for the CO_2 design than for the FC design, decreasing further with contraction of the CO_2 scale. The below-100% share for the optimal option is explained by the respondents' focus on rental price per day, rather than total financial costs. When the EFO is not financially optimal (case 2), its share drops significantly, but the pattern of differences across the metrics and scales is similar to the first case. In contrast to the first two cases, in the case when the EFO is not cost-minimizing but has the lowest rental price per day (case 3), it is more often chosen under the CO_2 design than under the FC design, with there being no significant differences among the CO_2 scales, on average.

Figure 4.2: Average predicted shares for the environmentally friendly option



NOTE: The figure depicts average choice shares of the environmentally friendly option and bootstrapped 95%-confidence interval computed from draws of the taste parameters for the FC and CO_2 designs.

The regression analysis offers a more formal investigation of the relationship between EFO choice shares and the characteristics of the choice sets and the framing of information, the results of which are given in Table 4.11. All effects have the expected signs. The results additionally show that in the case 3, the EFO choice shares under the CO_2 design with the most contracted scale (kg/km) are significantly different from the shares with CO_2 in g/km, after controlling for differences in financial and environmental costs and their interaction. The insignificant difference

[17]Summary statistics for the predicted shares of all three options in the simulated choice sets are available upon request.

between CO_2 in g/100 km and g/km could also be a result of left-digit bias – the tendency to ignore the rightmost digits of numerical information (e.g., Thomas and Morwitz, 2005; Manning and Sprott, 2009; Lacetera et al., 2012) that outweighs the scale effect in this case.

Overall, the results indicate that the share of the EFO is higher when its benefits in terms of the incurred financial costs and environmental characteristics are more apparent compared to the other option in the choice set, and differences in the monetary attributes are more important than the differences in the environmental costs. The results of the first two cases are in line with previous conclusions on the metric and scale effects – the EFO share is the highest under the FC design and the most expanded scale for the CO_2 design. The metric and scale effects also prevail in cases in which the fuel-efficient and environmentally friendly option is cost-minimizing. The third case additionally illustrates that when the EFO is not cost-minimizing but has the lowest price, the choice between two alternatives becomes more difficult for consumers, and in 50% of the cases, they select the option with the lowest price.

Table 4.11: Effects of choice set characteristics on choice shares of the environmentally friendly option

	Dependent Variable: $\ln(S_{EFO}) - \ln(1 - S_{EFO})$		
	Case 1 (Min EnvC & Min TC)	Case 2 (Min EnvC)	Case 3 (Min EnvC & Min P)
Design CO_2 (g/100 km)	0.186***	0.216***	−0.002
	(0.003)	(0.004)	(0.004)
Design CO_2 (kg/km)	−0.145***	−0.132***	−0.013***
	(0.003)	(0.004)	(0.004)
Design FC (l/100 km)	1.002***	0.643***	−0.185***
	(0.003)	(0.004)	(0.004)
$\triangle$EnvC	0.003***	0.006***	−0.002***
	(0.0001)	(0.0001)	(0.0002)
$\triangle$TC	0.012***	0.013***	−0.015***
	(0.0001)	(0.0001)	(0.0004)
Design CO_2 (g/100 km)×$\triangle$EnvC	0.001***	0.001***	−0.002***
	(0.0001)	(0.0001)	(0.0003)
Design CO_2 (kg/km)×$\triangle$EnvC	−0.001***	−0.001***	0.002***
	(0.0001)	(0.0001)	(0.0003)
Design FC (l/100 km)×$\triangle$EnvC	0.004***	0.004***	−0.006***
	(0.0001)	(0.0001)	(0.0003)
Design CO_2 (g/100 km)×$\triangle$TC	−0.001***	−0.001***	0.001
	(0.0002)	(0.0001)	(0.001)
Design CO_2 (kg/km)×$\triangle$TC	0.001***	0.0001	−0.0001
	(0.0002)	(0.0001)	(0.001)
Design FC (l/100 km)×$\triangle$TC	0.001***	0.004***	−0.005***
	(0.0002)	(0.0001)	(0.001)
$\triangle$EnvC×$\triangle$TC	0.00003***	−0.0001***	−0.0001***
	(0.00000)	(0.00000)	(0.00002)
Constant	−0.132***	−1.159***	0.062***
	(0.002)	(0.003)	(0.003)
Observations	42,792	80,568	4,780
Adjusted R^2	0.858	0.700	0.767
F Statistic	21,622.970***	15,655.500***	1,311.870***

NOTE: The dependent variable is the natural logarithm of the average EFO choice share relative to the shares of other options ($\ln(S_{EFO}) - \ln(1 - S_{EFO})$). To account for uncertainty in the dependent variable, the (feasible) generalized least squares regression is estimated with the weights being (squared) bootstrapped standard errors of the average choice shares. The regression analysis is performed for each case separately, pooling observations from the four designs. The reference category in each case is the CO_2 design (g/km). $\triangle$TC and $\triangle$EnvC refer to differences in the total financial and environmental costs between the first and the second options in the simulated choice sets, respectively. The total financial and environmental costs are computed for the whole trip (10 days; 2000 kilometers). $\triangle$TC and $\triangle$EnvC are mean-centered for each case. Standard errors are in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

4.6 General Discussion

The current study found significant metric and scale effects in consumer preferences for environmental benefits (i.e., hypotheses H1 and H2 are supported) but no differences in the investigated effects between two engine types (i.e., fail to reject the null hypothesis for H3) – the participants of the study value identical savings in fuel and CO_2 emissions differently but do so to the same extent for both engine types. Since relationships between metrics and scales and not average values are of interest, any hypothetical bias (Hensher, 2010) is of minor importance in this study, and the results are informative of the relative impact of the framing of information on choices.

The observed differences in WTP across metrics and scales relate to the premise of "bounded or limited rationality" that may manifest in limitations in individuals' ability to process information and limited personal experience (Simon, 1955). Prior research provides mixed evidence on the effects of individual education and knowledge and of information provision on pro-environmental behavior and the correct valuation of energy savings (Flamm, 2009; Meyer, 2015; Frederiks et al., 2015; van den Bergh, 2008). The present study found no significant effect of the completion of university education on the framing effects. In contexts similar to that of the current study, Camilleri and Larrick (2014) also found a statistically insignificant effect of consumers' numerical abilities on choices, and Cadario et al. (2016) showed that highly numerate individuals, for whom the framing of numerical information should have smaller effects (Peters et al., 2006), could even be more prone to the scale effect.

To test the importance of personal experience, the presence and magnitude of the metric and scale effects were also evaluated for the sample of individuals who have rental experience (63% of the full sample). The parameter estimates of the MXL model for this sample (Table 4.27) result in a lower overvaluation of fuel savings (WTP is closer to the actual fuel savings of €24) for the FC design but greater undervaluation of savings on the environmental costs for the CO_2 design. Although there is no significant scale effect for those with rental experience, the difference in WTP for identical improvements in FC and CO_2 is still present and constitutes €17 for one l/100 km, on average.

Scale effect. The scale effect occurs because people fail to take into account the unit in which quantitative information is expressed and, as a result, may perceive the CO_2 emissions on a contracted scale as being of lower and insignificant importance to the environment and personal decisions. Conversely, because perceptions of attribute differences tend to be inflated on expanded scales, consumers' sensitivity to losses or gains in attribute values increases. This difference in the evoked meaning of the CO_2 emissions on various scales is comparable to the denomination effect (Raghubir and Srivastava, 2009) but with the opposite conclusion. Under the denomination effect, consumers tend to value a certain amount of money more when it is expressed in fewer units or on a contracted scale (e.g., in euros) than in more units or on an expanded scale (e.g., in cents) despite their equivalence in monetary value. Thus, the findings in the current study indicate that the scale effect can also occur in situations in which the different types of units entail differences in associated meaning, in contrast to the suggestions by Pandelaere et al. (2011), who investigated scales with limited evoked meaning (e.g., a 1,000-point scale versus a 10-point scale).

The assignment of a higher weight to an attribute on expanded scales can also result from the perceived existence of intermediate levels. This is similar to the number-of-levels (NOL) effect that indicates an increased derived importance weight of an attribute as the number of intervening attribute levels increases (Wittink et al., 1990; Verlegh et al., 2002; Hensher, 2006). This distortion of attribute importance measures in favor of attributes with more levels might have significant consequences for product-related decisions. To mitigate the NOL effect, the present study equalized the number of levels for two quantitative characteristics in the choice experiments (the rental price and the metric). However, to distinguish between the scale and the NOL effects perceived by consumers, more research is needed that studies the underlying psychological causes of the two effects.

The observed differences in the WTP for CO_2 across three scales could also be affected by a default unit (or familiarity) effect – for some attributes, individuals could be accustomed to processing quantitative information in particular units (Lembregts and Pandelaere, 2013). For example, in Germany, the values of CO_2 emissions on car labels are expressed in g/km. If the default unit effect is present, then a product with CO_2 presented in g/km may generate a higher WTP despite its representation being more contracted compared to another scale. Whereas the higher WTP for CO_2 expressed in g/km compared to CO_2 in kg/km (the most contracted scale) could be a result of both the scale and default unit effects, the default and scale effects for CO_2 in g/100 km (the most expanded scale) compared to g/km have the opposite signs. Because the estimated WTP for CO_2 in g/100 km is higher on average than that for CO_2 in g/km, the default unit effect should be smaller than the scale effect in the present study. The importance of the default unit can also be assessed by examining participants' responses to a survey's question regarding what units they find the most convenient to understand a car's CO_2

emission values.[18] If individuals do not have a preference for a particular scale for the CO_2 information, then their answers to this question should be significantly affected by the CO_2 design they experienced in the choice experiment. On average, only approximately half of the respondents selected "g/km" as the preferred CO_2 scale. The other half of the respondents selected the same units as they encountered during the experiment – "g/100 km" and "kg/km" were 3.2 and 3.4 times more likely to be preferred, respectively, under the CO_2 design with the same CO_2 units than under other designs. These patterns also hold for individuals who have rental car experience or own a car and suggest that the default unit effect is not substantial for the respondents in this study.

Metric effect. The metric effect occurs because people perceive improvements in FC and CO_2 from different perspectives. Whereas consumers appear to directly associate improvements in FC with financial savings, they fail to perceive the link between reductions in CO_2 emissions and in FC. As a result, when presented with information on CO_2 emissions, consumers shift their focus to other monetary values (e.g., price) and may make suboptimal choices that yield higher financial and environmental costs. Regarding prior research on consumer perceptions of various metrics that convey the same information, Camilleri and Larrick (2014), for example, also observed that people tended to select a more fuel-efficient (and, thus, a more environmentally friendly) vehicle when fuel economy was expressed in terms of the fuel costs rather than the amount of fuel consumed, as consumers were primarily motivated to minimize their costs. Determining the effect of presenting the information in terms of fuel costs was not of interest in the present study, but the findings would most probably be replicated and could suggest a correct valuation of fuel savings.

However, there are also individuals who are interested in better fuel economy for reasons other than cost minimization, such as environmental attitudes. The effects of individual-specific variables on the metric and scale effects demonstrate that individuals with more knowledge and higher environmental concerns can better assess the potential benefits of a more fuel-efficient and environmentally friendly option. When confronted with CO_2 emissions instead of FC, environmentally consciousness individuals could also better align their choices with personal objectives (Ungemach et al., 2017). Thus, the current study also relates to the stream of literature on the determinants of pro-environmental behavior (Poortinga et al., 2004; Hines et al., 1987; Kollmuss and Agyeman, 2002) but analyzes decision-makers' choices instead of self-reported importance weights of environmental issues or intentions to engage in pro-environmental behavior. Greater environmental knowledge and environ-

[18]The question was asked after the choice experiments and had 7 response options: "g/km", "kg/km", "g/100 km", "kg/l", "g/l", "others", and "do not know".

mental concerns do not necessarily translate into pro-environmental behavior (the "attitude-action gap" and "knowledge-action gap"; Kollmuss and Agyeman, 2002; Frederiks et al., 2015). In the current study, participants evaluated their personal knowledge on climate issues as average and their perception of the importance of problems related to climate change as slightly higher than average (see Table 4.19). Both self-reported measures were uninformative in explaining differences in choices between levels of FC or CO_2. Therefore, the investigation of the observed choices provided a more accurate understanding of consumer behavior in terms of subsequent policy implications.

The values of FC may also be weighed more heavily (or be more salient) in the decision process than CO_2 emissions because consumers are more familiar with FC and thus may have some reference value to which they can compare the presented car offers (Bordalo et al., 2013; Busse et al., 2015). However, as the results demonstrate, if environmental issues become essential for consumers, and consumers are aware of the correlation between FC and CO_2, then CO_2 also becomes a salient attribute, and the valuations of the two attributes approach the actual values of fuel savings and environmental benefits.

Implications and future research. Taken as a whole, the findings of the present study provide several implications for managers and policy-makers and raise several avenues for future research. First, expansion of the scale for attributes related to environmental pollution, if wisely employed, could be used to nudge consumers' choices towards more fuel-efficient and low-emission car options (Camilleri and Larrick, 2014; Thaler and Sunstein, 2008). Doing so would be especially important when consumers have limited knowledge of the correlation between FC and CO_2 and lower environmental concerns. Although the current study finds no diminishing effect of scale expansion for the three investigated scales of CO_2 emissions (in contrast to Aribarg et al., 2017), the appropriateness of further expansion of the scale should be carefully investigated in each particular case. Having more units for the CO_2 values could lead to greater difficulties in processing the given numerical information even in the presence of the desired scale effect on consumer behavior. Future work could study in greater detail the interplay between scale expansion and ease of processing the provided information.

Second, as the present study shows, demand for vehicles with low FC and low emissions are driven by different preferences. If individuals are unaware of the correlation between these two metrics, they would fail to recognize how transport-related CO_2 emissions translate into 'private' costs and thus may end up incurring higher financial costs than under their optimal choices and cause higher environmental costs for society. Although a sensible choice architecture may nudge consumers in a financially and environmentally optimal direction, it would do so through intuitive and impulsive processes of the automatic thinking system and would not encourage an active change in behavior (Avineri, 2012). The results of this study suggest that it is crucial not only to provide information about transport-related CO_2 emissions to increase the likelihood of more sustainable choices by individuals but also to implement campaigns needed to stimulate knowledge, interest, and awareness of the personal impact on the environment when choosing energy-using and CO_2-emitting products.

The metric presented to consumers may also serve as a signpost that enables individuals to activate personal objectives aligned with societal goals (Ungemach et al., 2017) and thus help to reduce the attitude-behavior gap. With a better alignment of personal goals with choices, consumers may experience higher satisfaction from their product choice and usage. Consequently, depending on the product or service provided by a firm, higher satisfaction may lead to competitive and financial advantages through better firm image, higher customer loyalty, and repeat purchases from the firm (Miles and Covin, 2000). Further study on this premise is needed.

Furthermore, the type of metric used to express environmental benefits may affect consumers' processing of the given information. While information on FC may trigger consumer choices to be driven by cognition, that on CO_2 emissions may encourage the processing of numerical information to be driven by feelings. Thus, different types of information provision may suit each metric better for promoting more fuel-efficient and low-carbon choices – e.g., a promotion or prevention focus of the product message and rounded or nonrounded presentation of attribute levels (Wadhwa and Zhang, 2015; Grankvist et al., 2004). Future studies could test this assertion. Future research could also investigate whether detailed verbal cues, as opposed to numerical values, have a more significant positive impact on choices of more environmentally friendly car options, as Gleim et al. (2013) showed for green products in the retail setting.

Although the present study relied on the responses of respondents from various socio-demographic backgrounds (e.g., age, education, and income), it would also be beneficial for further research to target a representative population of consumers in a similar environmentally important context.

4.7 Conclusion

The current study presented empirical evidence on the metric and scale effects in willingness-to-pay for environmental benefits. An online survey with individuals from various socio-economic backgrounds presented optimally designed choice experiments in which individuals had to choose a car to rent for a long holiday trip. Differences in the importance of and willingness-to-pay for identical improvements in car characteristics related to environmental impacts were identified by varying the metrics (FC or CO_2) within subjects and the CO_2 scales between subjects.

The results replicated prior research on the positive value of scale expansion as a tool of choice architecture (Burson et al., 2009; Cadario et al., 2016; Camilleri and Larrick, 2014; Avineri, 2012; Pandelaere et al., 2011) and further revealed significant differences in consumer preferences for improvements in FC versus CO_2 values. In an extension of many previous studies, the metric and scale effects were assessed while accounting for observed and unobserved heterogeneity in tastes for attributes in addition to the respondents' environmental attitudes and knowledge. This led not only to better statistical model fit but also to significant differences in the recovered willingness-to-pay values compared to models without consumer heterogeneity and correlation in tastes for product attributes.

A reduction in CO_2 concentration is the principal objective of climate policies. However, as the present findings indicated, consumers may significantly undervalue the benefits of more fuel-efficient vehicles when presented information on CO_2. Under the most contracted CO_2 scale (in kg/km), individuals valued only 55% of the reduction in fuel or environmental costs. Because consumers do not understand the correlation between FC and CO_2, demand for vehicles with low fuel consumption and low emissions become two different decision-making processes – with a focus on either personal financial costs or societal environmental costs. Even in the absence of a conflict between a concern for environmental protection and a desire to reduce one's expenses, i.e., when the environmentally friendly product is also cost-minimizing, individuals were found to undervalue improvements in financially and environmentally important attributes if information on CO_2 emissions, instead of FC, was presented. However, CO_2 information on the most expanded scale (here, in g/100 km) was able to nudge individuals towards optimal choices and the correct valuations of fuel efficiency and environmental costs. The impact of individual-specific variables on the metric and scale effects further demonstrated that the proportion of fuel-efficient and environmentally friendly choices could be increased by activating pro-environmental attitudes and expanding consumers' knowledge of the environmental impact of vehicles.

As car rentals and various forms of collective car ownership are gaining popularity as an alternative to private cars and public transportation, it is increasingly important to make attributes with negative externalities, which might otherwise be neglected for these services, more salient. In summary, the current study provides insights for policy-makers and marketing managers on how to effectively communicate with consumers to facilitate the desired behavior.

4.8 Appendix

4.8.A Experimental design

This section provides details on the development of the choice experiment design used in this study. The combinations of attribute levels within tasks were identical for FC and CO_2 designs. Hence, it was only necessary to develop one experimental design. Table 4.12 shows how the D-efficiency varies among the designs with different numbers of choice tasks. The design with 14 tasks has higher D-efficiency than a design with 12 tasks and lower correlations for the attributes compared to the designs with 12 or 16 choice tasks. As a result, the experiment with 14 tasks was used in this study. Table 4.13 further confirms that the selected experimental design is efficient because all of the off-diagonal elements of the variance matrix are small relative to the variances on the diagonal. Tables 4.14 and 4.15 present the description of the 14 choice tasks with the corresponding total financial and environmental costs for each option in the tasks.

Table 4.16 provides the results of testing the experimental designs on the responses of 400 persons simulated according to random utility theory (McFadden, 1973; Train, 2009). For ease of interpretation, theoretical values for the parameters are expressed as willingness-to-pay values per day. The FC parameter corresponds to the actual fuel savings of €26 from one l/100 km for gasoline cars over 10 days and 2000 kilometers. The interaction term of FC and Diesel correspondents to the difference in fuel savings for gasoline and diesel vehicles. The parameters for CO_2 and its interaction with Diesel correspond to the actual reductions in CO_2 emissions from one g/km for gasoline (€1.12 over 10 days) and diesel vehicles (€0.83 over 10 days), respectively. The parameter for the no-choice option is set to result in its share of approximately 15%. The scale parameter μ transforms the utility in preference space into the utility in WTP-space and reflects how precise the respondents' choices between options are – the higher the μ, the higher the choice precision, while $\mu = 0$ suggests that the choices are made randomly. In the test of the experimental design, the scale parameter is set at the level of 0.3. This level corresponds to a reasonable value of the price elasticity evaluated at the average price and choice share. The results of 400 resamples of the simulated responses indicate that all parameter estimates can be efficiently recovered for the experimental designs.

Table 4.12: Efficiency characteristics of SAS designs with various numbers of choice tasks

Number of choice tasks	D-Efficiency	Canonical correlations				Correlation coefficients		
12	75.62		Engine	Price	Metric	Engine	Price	Metric
		Engine	1	0.59	0.24	1	0.35	0.06
		Price	0.59	1	0.55	0.35	1	0.30
		Metric	0.24	0.55	1	0.06	0.30	1
14	83.40		Engine	Price	Metric	Engine	Price	Metric
		Engine	1	0.29	0	1	0.08	0
		Price	0.29	1	0.58	0.08	1	0.34
		Metric	0	0.58	1	0	0.34	1
			Engine	Price	Metric	Engine	Price	Metric
16	89.11	Engine	1	0.35	0	1	0.12	0
		Price	0.35	1	0.61	0.12	1	0.37
		Metric	0	0.61	1	0	0.37	1

NOTE: “Engine” refers to the engine type and has two attribute levels (diesel and gasoline); “Price” is the rental price per day and has four attribute levels; “Metric” refers to either FC or CO_2 values and has four attribute levels.

Table 4.13: The variance-covariance matrix for the SAS design with 14 choice tasks

	Intercept	x1	x21	x22	x23	x31	x32	x33	x1*x31	x1*x32	x1*x33
Intercept	0.102	0.008	0.018	0.026	0.044	0.068	0	0	-0.005	0.013	-0.022
x1	0.008	0.086	0.018	0.026	0	0.014	0	0	0.023	-0.006	-0.011
x21	0.018	0.018	0.125	0	0	0.031	-0.044	0.026	-0.01	-0.015	-0.026
x22	0.026	0.026	0	0.125	0	0.044	0.031	-0.018	-0.015	-0.021	-0.036
x23	0.044	0	0	0	0.125	0.077	0	0	0	0.054	-0.031
x31	0.068	0.014	0.031	0.044	0.077	0.180	0	0	-0.008	0.022	-0.038
x32	0	0	-0.044	0.031	0	0	0.086	-0.014	0	0	0
x33	0	0	0.026	-0.018	0	0	-0.014	0.07	0	0	0
x1*x31	-0.005	0.023	-0.01	-0.015	0	-0.008	0	0	0.112	0.004	0.006
x1*x32	0.013	-0.006	-0.015	-0.021	0.054	0.022	0	0	0.004	0.091	-0.005
x1*x33	-0.022	-0.011	-0.026	-0.036	-0.031	-0.038	0	0	0.006	-0.005	0.086

NOTE: x1 is the first level of the attribute “engine type”; x21, x22, and x23 are the corresponding levels of the attribute “price per day”; x31, x32, and x33 are the corresponding levels of the metric (FC or CO_2). In an efficient design, all of the off-diagonal elements of the variance matrix should be small relative to the variances on the diagonal.

Table 4.14: FC design with total financial and environmental costs

Task	Engine 1	Price 1 (€/day)	FC 1 (l/100 km)	Engine 2	Price 2 (€/day)	FC 2 (l/100 km)	TC[(a)] 1 (€)	TC[(a)] 2 (€)	EnvC[(b)] 1 (CO_2 kg)	EnvC[(b)] 2 (CO_2 kg)
1	Diesel	33	5.2	Gasoline	30	6.2	444.40	461.20	275.60	287.68
2	Diesel	30	4.2	Gasoline	26	5.2	392.40	395.20	222.60	241.28
3	Diesel	26	5.2	Diesel	30	3.2	374.40	370.40	275.60	169.60
4	Gasoline	30	5.2	Diesel	33	4.2	435.20	422.40	241.28	222.60
5	Gasoline	23	4.2	Diesel	26	3.2	339.20	330.40	194.88	169.60
6	Gasoline	26	5.2	Gasoline	30	3.2	395.20	383.20	241.28	148.48
7	Gasoline	33	3.2	Diesel	30	6.2	413.20	436.40	148.48	328.60
8	Diesel	33	6.2	Gasoline	33	5.2	466.40	465.20	328.60	241.28
9	Gasoline	26	4.2	Gasoline	23	6.2	369.20	391.20	194.88	287.68
10	Gasoline	23	3.2	Diesel	23	4.2	313.20	322.40	148.48	222.60
11	Gasoline	33	6.2	Diesel	33	6.2	491.20	466.40	287.68	328.60
12	Diesel	30	3.2	Gasoline	23	6.2	370.40	391.20	169.60	287.68
13	Diesel	23	3.2	Gasoline	23	3.2	300.40	313.20	169.60	148.48
14	Diesel	33	4.2	Diesel	30	6.2	422.40	436.40	222.60	328.60

NOTE: (a) The total financial costs are $TC = (€/Day) \times Days + FC \times FP \times KM$. (b) The environmental costs are $EnvC = CO_2 \times KM$.

Table 4.15: CO_2 (g/km) design with total financial and environmental costs

Task	Engine 1	Price 1 (€/day)	CO_2 1 (g/km)	Engine 2	Price 2 (€/day)	CO_2 2 (g/km)	$TC^{(a)}$ 1 (€)	$TC^{(a)}$ 2 (€)	$EnvC^{(b)}$ 1 (CO_2 kg)	$EnvC^{(b)}$ 2 (CO_2 kg)
1	Diesel	33	138	Gasoline	30	164	444.57	483.79	276.00	328.00
2	Diesel	30	111	Gasoline	26	138	392.15	414.66	222.00	276.00
3	Diesel	26	138	Diesel	30	85	374.57	370.57	276.00	170.00
4	Gasoline	30	138	Diesel	33	111	454.66	422.15	276.00	222.00
5	Gasoline	23	111	Diesel	26	85	354.40	330.57	222.00	170.00
6	Gasoline	26	138	Gasoline	30	85	414.66	395.26	276.00	170.00
7	Gasoline	33	85	Diesel	30	164	425.26	436.15	170.00	328.00
8	Diesel	33	164	Gasoline	33	111	466.15	454.40	328.00	222.00
9	Gasoline	26	111	Gasoline	23	164	384.40	413.79	222.00	328.00
10	Gasoline	23	85	Diesel	23	111	325.26	322.15	170.00	222.00
11	Gasoline	33	164	Diesel	33	164	513.79	466.15	328.00	328.00
12	Diesel	30	85	Gasoline	23	164	370.57	413.79	170.00	328.00
13	Diesel	23	85	Gasoline	23	85	300.57	325.26	170.00	170.00
14	Diesel	33	111	Diesel	30	164	422.15	436.15	222.00	328.00

NOTE: Designs for other CO_2 scales differ only in presentation of the CO_2 emission values and are identical to the presented CO_2 design for g/km values in terms of total financial and environmental costs. (a) The total financial costs are $TC = (€/Day) \times Days + FC \times FP \times KM$. (b) The environmental costs are $EnvC = CO_2 \times KM$.

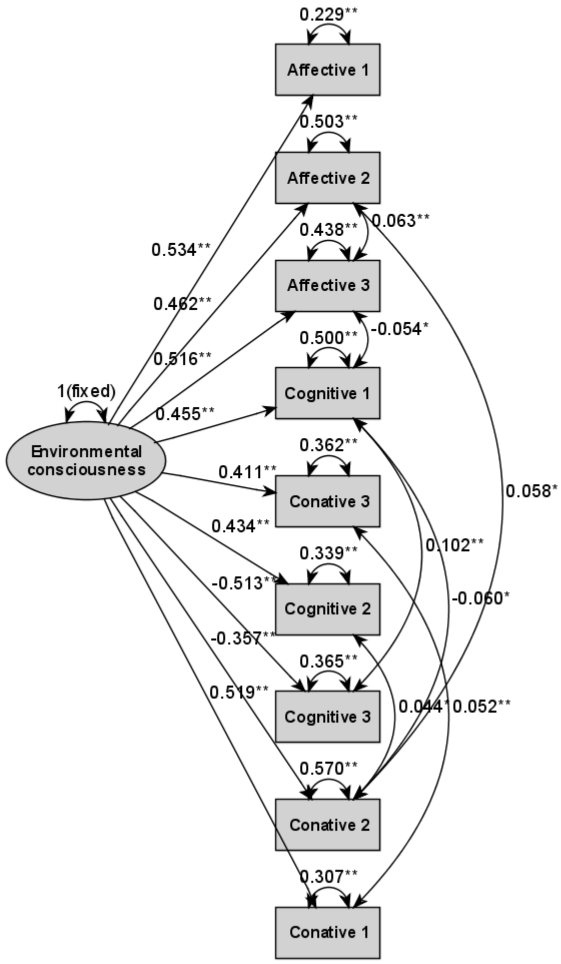
Table 4.16: Test of the experimental design on simulated choices

	FC design				CO_2 design		
	Theoretical values	MNL estimates (nR = 400) Mean	SE		Theoretical values	MNL estimates (nR = 400) Mean	SE
μ	0.300	0.299	0.013	μ	0.300	0.301	0.014
no-choice	-45.000	-45.064	0.491	no-choice	-45.000	-44.993	0.531
Diesel	1.000	1.018	0.512	Diesel	1.000	1.002	0.519
FC	-2.600	-2.611	0.085	CO_2	-0.112	-0.112	0.004
FC×Diesel	0.400	0.398	0.107	CO_2×Diesel	0.029	0.029	0.004
log-likelihood		-4964.189	35.115	log-likelihood		-4790.984	39.892
Choice Shares	Option 1	Option 2	No-choice option	Choice Shares	Option 1	Option 2	No-choice option
	45.32	40.55	14.13		44.89	39.11	16.00

NOTE: nR is the number of samples with 400 persons simulated according to random utility theory. μ is the scale parameter to transform the utility in preference space into the utility in WTP-space. All parameters are euro values per day of the trip for marginal improvements in attributes.

4.8.B Individual-specific variables

Figure 4.3: Path diagram for the "General Environmental Consciousness" scale



NOTE: The scale is based on UBA (2016) with response options ranging from 1: Strongly disagree to 4: Strongly agree. Based on the percentile method with 1000 bootstrap resamples of the size 400 from the initial 586 observations, the average Cronbachs α is 0.83 and the bootstrap confidence interval ranges from 0.80 to 0.86. $\chi^2(p) = 24.699$ (0.213); RMSEA= 0.020; AGFI= 0.980.

Table 4.17: Indicators related to environmental attitudes, perception of a car use, and knowledge

	Wording	Source	Variable
General Environmental Consciousness			
1.	If things continue on their present course, we will soon experience a major ecological catastrophe.	UBA (2016)	"Affective 1"
2.	When I read newspaper reports or watch TV broadcasts on environmental problems, I get frustrated and angry.	UBA (2016)	"Affective 2"
3.	It worries me to think about the environmental conditions, under which our children and grandchildren would probably have to live.	UBA (2016)	"Affective 3"
4.	There is a limit to the economic growth that our industrialized world has already crossed or will reach very soon.	UBA (2016)	"Cognitive 1"
5.	It is still the case that politicians are doing far too little for environmental protection.	UBA (2016)	"Cognitive 2"
6.	In my assessment, the so-called "ecological crisis" facing humankind has been greatly exaggerated by many environmentalists.	UBA (2016)	"Cognitive 3"
7.	For the benefit of the environment, we should all be prepared to restrict our current standard of living.	UBA (2016)	"Conative 1"
8.	Science and technological progress will solve many environmental problems without a need to change our way of life.	UBA (2016)	"Conative 2"
9.	Measures to protect the environment should be enforced even if this results in lost jobs.	UBA (2016)	"Conative 3"
Perception of a car use			
10.	Even if public transportation was more efficient than it is, I would prefer to drive my own car.	Milfont and Duckitt (2010)	"Cars preferred"
11.	People exaggerate the role of car traffic as the cause for climate change.	Peters et al. (2011)	"Cars as non-cause"
Financial motive			
12.	For me, improvements in fuel consumption of a car are foremost linked to savings in my expenses.	Own	"Financial motive"
13.	I am willing to pay higher prices for products that are less polluting.	Own	"WTP for less pollution"
Knowledge			
14.	Burning fossil fuels such as, for instance, gas and oil raises CO_2 levels in the atmosphere.	Kaiser et al. (1999)	
15.	It is possible to improve the fuel consumption of a car, while keeping its CO_2 emission constant.	Own	"FC-CO_2 knowledge"
16.	The burning of one liter of diesel does more harm to the environment and climate than the burning of one liter of petrol (gasoline).	Own	"Diesel perception"

NOTE: Response options for all items included "strongly disagree", "somewhat disagree", "somewhat agree", "strongly agree", and "do not know". Statements 1-9 belong to the "General Environmental Consciousness" (GEC) scale.

Table 4.18: Percentage distributions for variables related to environmental attitudes, perception of a car use, and knowledge

Item	SD	SWD	SWA	SA	DnK
General Environmental Consciousness					
1. If things continue on their present course, we will soon experience a major ecological catastrophe.	2.59	8.87	36.6	48.8	3.14
2. When I read newspaper reports or watch TV broadcasts on environmental problems, I get frustrated and angry.	6.84	23.29	37.89	27.73	4.25
3. It worries me to think about the environmental conditions, under which our children and grandchildren would probably have to live.	5.73	14.23	36.6	41.59	1.85
4. There is a limit to the economic growth that our industrialized world has already crossed or will reach very soon.	6.84	15.71	33.83	33.46	10.17
5. It is still the case that politicians are doing far too little for environmental protection.	2.40	10.17	36.23	49.17	2.03
6. In my assessment, the so-called "ecological crisis" facing humankind has been greatly exaggerated by many environmentalists.	49.63	30.22	13.43	3.54	3.17
7. For the benefit of the environment, we should all be prepared to restrict our current standard of living.	3.54	16.42	43.66	33.21	3.17
8. Science and technological progress will solve many environmental problems without a need to change our way of life.	15.86	34.89	31.53	11.01	6.72
9. Measures to protect the environment should be enforced even if this results in lost jobs.	4.66	17.72	45.34	21.83	10.45
Perception of a car use					
10. Even if public transportation was more efficient than it is, I would prefer to drive my own car.	41.42	29.85	16.42	10.07	2.24
11. People exaggerate the role of car traffic as the cause for climate change.	43.44	32.53	13.86	7.02	3.14
Financial motive					
12. For me, improvements in fuel consumption of a car are foremost linked to savings in my expenses.	7.76	27.91	38.63	18.48	7.21
13. I am willing to pay higher prices for products that are less polluting.	3.73	20.15	47.01	25.00	4.10
Knowledge					
14. Burning fossil fuels such as, for instance, gas and oil raises CO_2 levels in the atmosphere.	0.74	2.77	27.36	63.77	5.36
15. It is possible to improve the fuel consumption of a car, while keeping its CO_2 emission constant.	2.99	8.96	32.09	12.69	43.28
16. The burning of one liter of diesel does more harm to the environment and climate than the burning of one liter of petrol (gasoline).	5.22	15.67	29.29	12.31	37.5

NOTE: SD is "Strongly disagree"; SWD is "somewhat disagree"; SWA is "somewhat agree"; SA is "strongly agree"; and DnK is "do not know".

Table 4.19: Percentage distributions and average responses to the self-reported knowledge and importance of issues related to climate change

	Percentage distribution							Mean (SE)
How well informed would you say you are about issues related to climate change?[a]	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
	0	2.62	13.64	35.51	34.77	11.96	1.50	4.44 (0.04)
How important is the issue of climate change to you personally?[b]	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
	0.93	2.99	7.29	16.82	30.28	29.53	12.15	5.10 (0.06)

NOTE: (a) The wording of response options was (1): Not at all; (2): Very poorly; (3): Poorly; (4): Average; (5): Well; (6): Quite well; (7): Expertly. (b) The wording of response options was (1): Not at all; (4): Average; (7): Extremely.

Table 4.20: Definitions of the individual-specific variables

Variable	Definition
1. Male	= 1 if male, else 0
2. Age	Years old of a person
3. Kids under 18	= 1 if a person has children younger than 18 years old, else 0
4. University degree	= 1 if a person has a completed university degree, else 0
5. Own car/-s	= 1 if a person owns one or more cars, else 0
6. Income	A group for the personal net monthly income (1 =“<€500”; 2 =“€500 to under €1000”; 3 =“€1000 to under €1500”; 4 =“€1500 to under €2000”; 5 =“€2000 to under €3000”; 6 =“€3000 to under €4000”; 7 =“≥€4000”; 8 =“Prefer not to answer”)
7. Rental experience	= 1 if a person has a rental experience, else 0
8. GEC	A score from the confirmatory factor analysis for the “General Environmental Consciousness” scale
9. “WTP for less pollution”	= 1 if a person responded “somewhat agree” or “strongly agree” to the statement (13) in Table 4.18, else 0
10. “Financial motive”	= 1 if a person responded “somewhat agree” or “strongly agree” to the statement (12) in Table 4.18, else 0
11. “Cars as non-cause”	= 1 if a person responded “somewhat agree” or “strongly agree” to the statement (11) in Table 4.18, else 0
12. “Cars preferred”	= 1 if a person responded “somewhat agree” or “strongly agree” to the statement (10) in Table 4.18, else 0
13. “Diesel perception”	= 1 if a person responded “somewhat agree” or “strongly agree” to the statement (16) in Table 4.18, else 0
14. “FC-CO_2 knowledge”	= 1 if a person responded “somewhat disagree” or “strongly disagree” to the statement (15) in Table 4.18, else 0

Table 4.21: Correlation among individual-specific variables

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Male													
2. Age	0.093***												
3. Kids under 18	0.021***	0.269***											
4. University degree	-0.031***	0.245***	0.126***										
5. Own car/-s	-0.059***	0.252***	0.255***	0.042***									
6. Income	0.134***	0.395***	0.312***	0.398***	0.195***								
7. Rental experience	0.087***	0.375***	0.118***	0.257***	0.107***	0.239***							
8. GEC (score)	-0.233***	-0.057***	-0.111***	-0.124***	-0.186***	-0.106***	-0.057***						
9. “WTP for less pollution”	-0.152***	0.014**	0.004	-0.033***	-0.095***	-0.126***	-0.038***	0.400***					
10. “Financial motive”	0.049***	-0.050***	0.037***	0.017**	-0.022***	-0.058***	0.027***	-0.175***	-0.133***				
11. “Cars as non-cause”	0.104***	0.107***	0.041***	0.085***	0.182***	0.120***	0.008	-0.434***	-0.223***	0.094***			
12. “Cars preferred”	0.072***	0.033***	0.130***	-0.001	0.348***	0.126***	0.005	-0.271***	-0.212***	0.057***	0.238***		
13. “Diesel perception”	0.112***	0.069***	-0.002	0.012*	0.097***	0.008	0.042***	0.054***	-0.033***	0.012*	0.002	0.051***	
14. “FC-CO_2 knowledge”	0.103***	0.035***	-0.037***	0.004	0.062***	0.070***	-0.052***	-0.154***	-0.104***	-0.014**	0.155***	0.092***	0.063***

NOTE: Reported are the coefficients for the Pearson correlation for continuous variables and the tetrachoric correlation for dichotomous variables. GEC refers to the General Environmental Consciousness scale. *p<0.1; **p<0.05; ***p<0.01.

4.8.C Additional tables

Table 4.22: MNL parameter estimates (FC design)

	Dependent variable: Choice			
	(1)	(2)	(3)	(4)
Price	−0.099***	−0.102***	−0.091***	−0.091***
	(0.013)	(0.014)	(0.015)	(0.015)
Price×(Income less than average)			−0.008	−0.011**
			(0.007)	(0.005)
Price×(Income more than average)			−0.021***	−0.019***
			(0.007)	(0.006)
Diesel	−0.103	−0.091	−0.091	−0.091
	(0.123)	(0.128)	(0.129)	(0.129)
none	−8.646***	−8.873***	−8.869***	−8.875***
	(0.522)	(0.562)	(0.562)	(0.562)
FC	−0.676***	−0.649***	−0.686***	−0.684***
	(0.029)	(0.035)	(0.039)	(0.031)
FC×Diesel	−0.001	−0.006	−0.006	−0.006
	(0.026)	(0.027)	(0.027)	(0.027)
FC×(First CO_2 design)		−0.038*	−0.038*	−0.037*
		(0.019)	(0.019)	(0.019)
FC×Male		0.0001	0.003	0.002
		(0.020)	(0.020)	(0.020)
FC×Age		0.001	−0.001	0.001
		(0.001)	(0.002)	(0.001)
FC×Age^2			0.0001	
			(0.0001)	
FC×(University degree)		0.087***	0.100***	0.097***
		(0.022)	(0.024)	(0.021)
FC×(Own car-/s)		−0.009	−0.007	−0.002
		(0.022)	(0.023)	(0.021)
FC×(Income less than average)		−0.046*	−0.026	
		(0.025)	(0.034)	
FC×(Income more than average)		−0.044	0.020	
		(0.029)	(0.037)	
FC×(Rental experience)		0.101***	0.110***	0.102***
		(0.022)	(0.023)	(0.022)
FC×GEC		−0.023**	−0.022**	−0.026***
		(0.010)	(0.010)	(0.009)
FC×(WTP for less pollution)		−0.028	−0.027	−0.029
		(0.026)	(0.026)	(0.025)
FC×(Financial motive)		−0.012	−0.011	−0.011
		(0.020)	(0.020)	(0.020)
FC×(Cars as non-cause)		0.013	0.012	
		(0.028)	(0.028)	
FC×(Cars preferred)		0.012	0.012	
		(0.024)	(0.024)	
FC×(Diesel perception)		−0.022	−0.023	−0.022
		(0.020)	(0.020)	(0.020)
FC×(FC-CO_2 knowledge)		−0.034	−0.031	−0.031
		(0.030)	(0.030)	(0.030)
Observations	7,950	7,280	7,280	7,280
Log Likelihood	-6,021.341	-5,441.049	-5,435.846	-5,437.465
Akaike Inf. Crit.	12,052.680	10,922.100	10,917.690	10,910.930

NOTE: All individual-specific variables but income are mean-centered. The average income group serves as a reference. *p<0.1; **p<0.05; ***p<0.01.

Table 4.23: MNL parameter estimates (CO_2 design)

	Dependent variable: Choice			
	(1)	(2)	(3)	(4)
Price	−0.162***	−0.156***	−0.145***	−0.148***
	(0.013)	(0.014)	(0.015)	(0.015)
Price×(Income less than average)			−0.012**	−0.010**
			(0.006)	(0.005)
Price×(Income more than average)			−0.023***	−0.017***
			(0.007)	(0.006)
Price×(CO_2 design, g/km)	−0.002	0.003	0.005	0.004
	(0.005)	(0.006)	(0.006)	(0.006)
Price×(CO_2 design, kg/km)	−0.021***	−0.018***	−0.017***	−0.018***
	(0.005)	(0.006)	(0.006)	(0.006)
none	−8.886***	−9.075***	−9.073***	−9.078***
	(0.506)	(0.542)	(0.542)	(0.542)
Diesel	−0.099	−0.098	−0.099	−0.098
	(0.121)	(0.126)	(0.126)	(0.126)
CO_2	−0.155***	−0.142***	−0.157***	−0.146***
	(0.012)	(0.014)	(0.015)	(0.013)
CO2×(CO_2 design, g/km)	0.015	0.010	0.009	0.011
	(0.010)	(0.011)	(0.011)	(0.011)
CO2×(CO_2 design, kg/km)	0.070***	0.056***	0.055***	0.056***
	(0.010)	(0.011)	(0.011)	(0.011)
CO2×Diesel	0.016*	0.013	0.013	0.013
	(0.010)	(0.010)	(0.010)	(0.010)
CO2×(First CO_2 design)		0.031***	0.032***	0.032***
		(0.007)	(0.007)	(0.007)
CO2×Male		0.043***	0.044***	0.044***
		(0.007)	(0.008)	(0.007)
CO2×Age		−0.001***	−0.002***	−0.001**
		(0.0004)	(0.001)	(0.0004)
CO2×Age^2			0.00003	
			(0.00002)	
CO2×(University degree)		0.049***	0.054***	0.053***
		(0.008)	(0.008)	(0.007)
CO_2×(Own car-/s)		0.013	0.014*	0.018**
		(0.008)	(0.008)	(0.008)
CO_2×(Income less than average)		−0.009	0.003	
		(0.009)	(0.011)	
CO_2×(Income more than average)		−0.0004	0.023*	
		(0.011)	(0.013)	
CO_2×(Rental experience)		0.027***	0.030***	0.027***
		(0.008)	(0.008)	(0.008)
CO_2×GEC		−0.021***	−0.020***	−0.023***
		(0.004)	(0.004)	(0.004)
CO_2×(WTP for less pollution)		−0.132***	−0.130***	−0.133***
		(0.012)	(0.012)	(0.012)
CO_2×(Financial motive)		0.025***	0.026***	0.026***
		(0.007)	(0.007)	(0.007)
CO_2×(Cars as non-cause)		0.012	0.012	
		(0.011)	(0.011)	
CO_2×(Cars preferred)		0.010	0.011	
		(0.009)	(0.009)	
CO_2×(Diesel perception)		−0.014**	−0.015**	−0.015**
		(0.007)	(0.007)	(0.007)
CO_2×(FC-CO_2 knowledge)		−0.030***	−0.029***	−0.029***
		(0.011)	(0.011)	(0.011)
Observations	7,757	7,280	7,280	7,280
Log Likelihood	-6,461.606	-5,771.973	-5,765.251	-5,769.501
Akaike Inf. Crit.	12,941.210	11,591.950	11,584.500	11,583.000

NOTE: All individual-specific variables but income are mean-centered. The average income group serves as a reference. *p<0.1; **p<0.05; ***p<0.01.

Table 4.24: MXL parameter estimates (full sample)

	Dependent Variable: Choice	
	(1) FC design	(2) CO_2 design
NegPrice	−1.135***	−1.013***
	(0.100)	(0.073)
none	−29.393***	−37.277***
	(1.649)	(1.778)
Diesel	0.179	0.339***
	(0.116)	(0.129)
NegFC	0.367***	
	(0.049)	
NegCO2		−1.066***
		(0.076)
NegPrice×(CO_2 design, g/km)		0.107***
		(0.026)
NegPrice×(CO_2 design, kg/km)		0.138***
		(0.040)
NegPrice×(Income less than average)	0.055	0.138***
	(0.052)	(0.030)
NegPrice×(Income more than average)	0.081	0.202***
	(0.053)	(0.048)
NegFC×(First CO_2 design)	−0.022	
	(0.048)	
NegFC×Male	0.115**	
	(0.048)	
NegFC×(University degree)	−0.044	
	(0.047)	
NegFC×(Rental experience)	−0.168***	
	(0.054)	
NegFC×GEC	0.068***	
	(0.021)	
NegFC×(WTP for less pollution)	0.136**	
	(0.063)	
NegFC×(Financial motive)	−0.002	
	(0.051)	
NegFC×(Diesel perception)	0.014	
	(0.061)	
NegFC×(FC-CO2 knowledge)	−0.013	
	(0.076)	
NegCO2×(CO_2 design, g/km)		−0.203***
		(0.057)
NegCO2×(CO_2 design, kg/km)		−0.438***
		(0.065)
NegCO2×(First CO_2 design)		−0.329***
		(0.058)
NegCO2×Male		−0.009
		(0.045)
NegCO2×(University degree)		−0.310***
		(0.045)
NegCO2×(Rental experience)		−0.221***
		(0.054)
NegCO2×GEC		0.239***
		(0.032)
NegCO2×(WTP for less pollution)		1.170***
		(0.114)
NegCO2×(Financial motive)		−0.246***
		(0.063)
NegCO2×(Diesel perception)		0.083
		(0.053)
NegCO2×(FC-CO2 knowledge)		0.341***
		(0.087)

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	Dependent variable: Choice	
	(1) FC design	(2) CO_2 design
sd.NegPrice.NegPrice	0.607***	−0.806***
	(0.030)	(0.028)
sd.NegPrice.none	−9.563***	23.071***
	(0.761)	(1.382)
sd.NegPrice.Diesel	0.976***	−1.092***
	(0.144)	(0.160)
sd.NegPrice.NegFC	−0.002	
	(0.036)	
sd.NegPrice.NegCO2		0.066
		(0.041)
sd.none.none	−8.464***	−12.290***
	(0.617)	(0.804)
sd.none.Diesel	−0.058	−0.219
	(0.165)	(0.173)
sd.none.NegFC	0.513***	
	(0.039)	
sd.none.NegCO2		0.738***
		(0.030)
sd.Diesel.Diesel	2.146***	2.551***
	(0.116)	(0.132)
sd.Diesel.NegFC	0.337***	
	(0.025)	
sd.NegFC.NegFC	0.065	
	(0.045)	
sd.Diesel.NegCO2		0.236***
		(0.036)
sd.NegCO2.NegCO2		0.322***
		(0.028)
Observations	7,280	7,280
Log Likelihood	-4,244.401	-4,192.690
Akaike Inf. Crit.	8,538.802	8,443.381
Bayesian Inf. Crit.	8,711.124	8,643.274

NOTE: The estimation of random coefficient logit model is based on maximum simulated likelihood method using the "gmnl" R package (version 1.1-3). Optimization of the log-likelihood is by BFGS maximization method. Simulation is based on 2000 Halton draws. Price, FC, and CO_2 enter the model as negative values. Individual-specific variables are mean-centered. *p<0.1; **p<0.05; ***p<0.01.

Table 4.25: Empirical correlation in taste parameters for attributes

	Price	None	Diesel	Metric
	FC design			
Price	1	0.68	-0.37	-0.02
None	0.68	1	-0.29	0.48
Diesel	-0.37	-0.29	1	-0.44
Metric	-0.02	0.48	-0.44	1
	CO_2 design			
Price	1	0.74	-0.27	0.09
None	0.74	1	-0.30	0.47
Diesel	-0.27	-0.30	1	-0.01
Metric	0.09	0.47	-0.01	1

Table 4.26: Differences in the WTP for identical improvements in FC and CO_2 for various population sub-groups

Gender	GEC	Financial motive	Rental experience	FC-CO_2 knowledge	mean	SE
Male	Low GEC	Yes	No	No	36.21	5.67
Male	Average GEC	Yes	No	No	35.92	5.86
Male	High GEC	Yes	No	No	34.84	6.35
Male	Low GEC	No	No	No	32.32	6.09
Male	Low GEC	Yes	Yes	No	31.06	4.04
Male	Average GEC	Yes	Yes	No	30.98	4.24
Male	Average GEC	No	No	No	30.94	6.23
Female	Low GEC	Yes	No	No	30.56	4.83
Male	High GEC	Yes	Yes	No	30.30	4.76
Female	Average GEC	Yes	No	No	29.85	4.97
Male	Low GEC	Yes	No	Yes	29.64	6.54
Male	High GEC	No	No	No	28.47	6.69
Female	High GEC	Yes	No	No	28.33	5.40
Male	Low GEC	No	Yes	No	27.97	4.35
Male	Average GEC	Yes	No	Yes	27.73	7.01
Male	Average GEC	No	Yes	No	27.02	4.50
Female	Low GEC	No	No	No	26.66	5.46
Female	Low GEC	Yes	Yes	No	26.33	3.58
Female	Average GEC	Yes	Yes	No	25.91	3.75
Male	Low GEC	Yes	Yes	Yes	25.80	4.99
Male	High GEC	No	Yes	No	25.22	4.98
Female	Average GEC	No	No	No	24.85	5.58
Female	High GEC	Yes	Yes	No	24.85	4.23
Male	High GEC	Yes	No	Yes	24.61	7.88
Male	Average GEC	Yes	Yes	Yes	24.44	5.45
Male	Low GEC	No	No	Yes	24.07	6.85
Female	Low GEC	Yes	No	Yes	24.04	5.74
Female	Low GEC	No	Yes	No	23.23	4.07
Male	High GEC	Yes	Yes	Yes	22.11	6.30
Female	High GEC	No	No	No	21.93	6.01
Female	Average GEC	No	Yes	No	21.93	4.22
Female	Average GEC	Yes	No	Yes	21.72	6.17
Male	Low GEC	No	Yes	Yes	21.36	5.20
Female	Low GEC	Yes	Yes	Yes	21.12	4.51
Male	Average GEC	No	No	Yes	20.62	7.32
Female	High GEC	No	Yes	No	19.76	4.69
Female	Average GEC	Yes	Yes	Yes	19.41	4.95
Male	Average GEC	No	Yes	Yes	18.77	5.68
Female	Low GEC	No	No	Yes	18.45	6.27
Female	High GEC	Yes	No	Yes	18.14	7.02
Female	High GEC	Yes	Yes	Yes	16.70	5.77
Female	Low GEC	No	Yes	Yes	16.67	4.91
Male	High GEC	No	No	Yes	15.52	8.28
Male	High GEC	No	Yes	Yes	14.87	6.62
Female	Average GEC	No	No	Yes	14.57	6.74
Female	Average GEC	No	Yes	Yes	13.72	5.39
Female	High GEC	No	Yes	Yes	9.43	6.36

NOTE: The average values of the metric effect for various sub-groups of interest are presented, with standard errors computed based on 300 bootstrap resamples of draws from the distribution of the taste parameters. The metric effect is given by differences in the WTP for 1 l/100 km computed for the FC design and CO_2 design (in g/km), for both engine types on average: ΔWTP(FC-CO_2) = WTP(FC) - WTP(CO_2, g/km)$\times$25. All other individual-specific variables are held at their sample averages.

Table 4.27: MXL parameter estimates (sample with rental experience)

	Dependent variable: Choice	
	(1) FC design	(2) CO_2 design
NegPrice	−0.534***	−0.802***
	(0.098)	(0.098)
none	−51.236***	−50.207***
	(3.379)	(3.074)
Diesel	0.523***	0.698***
	(0.146)	(0.176)
NegFC	0.605***	
	(0.059)	
NegCO2		−1.186***
		(0.109)
NegPrice×(CO_2 design, g/km)		−0.037
		(0.053)
NegPrice×(CO_2 design, kg/km)		−0.043
		(0.049)
NegPrice×(Income less than average)	−0.008	0.380***
	(0.073)	(0.044)
NegPrice×(Income more than average)	−0.004	0.169**
	(0.072)	(0.069)
NegFC×(First CO_2 design)	0.001	
	(0.052)	
NegFC×Male	0.106**	
	(0.053)	
NegFC×(University degree)	−0.073	
	(0.055)	
NegFC×GEC	0.060**	
	(0.025)	
NegFC×(WTP for less pollution)	0.132**	
	(0.065)	
NegFC×(Financial motive)	−0.041	
	(0.060)	
NegFC×(Diesel perception)	0.124**	
	(0.059)	
NegFC×(FC-CO_2 knowledge)	−0.037	
	(0.093)	
NegCO2×(CO_2 design, g/km)		−0.204**
		(0.084)
NegCO2×(CO_2 design, kg/km)		−0.268***
		(0.069)
NegCO2×(First CO_2 design)		−0.576***
		(0.060)
NegCO2×Male		−0.677***
		(0.073)
NegCO2×(University degree)		−0.497***
		(0.053)
NegCO2×GEC		0.353***
		(0.041)
NegCO2×(WTP for less pollution)		1.110***
		(0.125)
NegCO2×(Financial motive)		−0.040
		(0.064)
NegCO2×(Diesel perception)		0.151***
		(0.056)
NegCO2×(FC-CO_2 knowledge)		0.138
		(0.098)

Continues on the next page

	Dependent Variable: Choice	
	(1) FC design	(2) CO_2 design
sd.NegPrice.NegPrice	-0.648^{***}	0.856^{***}
	(0.032)	(0.037)
sd.NegPrice.none	24.788^{***}	-23.862^{***}
	(1.903)	(1.641)
sd.NegPrice.Diesel	-0.727^{***}	1.272^{***}
	(0.148)	(0.195)
sd.NegPrice.NegFC	-0.343^{***}	
	(0.034)	
sd.NegPrice.NegCO2		0.003
		(0.031)
sd.none.none	-0.574^{**}	-14.773^{***}
	(0.287)	(1.165)
sd.none.Diesel	2.213^{***}	-0.290
	(0.144)	(0.235)
sd.none.NegFC	0.232^{***}	
	(0.033)	
sd.none.NegCO2		0.723^{***}
		(0.027)
sd.Diesel.Diesel	0.253	2.726^{***}
	(0.297)	(0.169)
sd.Diesel.NegFC	-0.191^{***}	
	(0.032)	
sd.NegFC.NegFC	0.414^{***}	
	(0.035)	
sd.Diesel.NegCO2		0.130^{***}
		(0.031)
sd.NegCO2.NegCO2		0.626^{***}
		(0.047)
Observations	4,620	4,620
Number of persons	362	354
Log Likelihood	-2,681.846	-2,588.445
Akaike Inf. Crit.	5,411.691	5,232.889
Bayesian Inf. Crit.	5,566.207	5,413.158

NOTE: The estimation of random coefficient logit model is based on maximum simulated likelihood method using the "gmnl" R package (version 1.1-3). Optimization of the log-likelihood is by BFGS maximization method. Simulation is based on 2000 Halton draws. Price, FC, and CO_2 enter the model as negative values. Individual-specific variables are mean-centered. *p<0.1; **p<0.05; ***p<0.01.

Table 4.28: WTP (€) for FC and CO_2 (MXL model: sample with rental experience)

Attribute / Design	FC (1 l/100 km)					CO_2 (1 g/km)				
	Median	SE	SD	2.5%	97.5%	Median	SE	SD	2.5%	97.5%
FC (l/100 km)	**-31.31**	**2.35**	**24.69**	**-36.40**	**-27.02**	-1.25	0.09	0.99	-1.46	-1.08
CO_2 (g/100 km)	-17.38	2.25	81.97	-22.18	-13.51	**-0.70**	**0.09**	**3.28**	**-0.89**	**-0.54**
CO_2 (g/km)	-14.68	2.00	69.48	-18.58	-11.36	**-0.59**	**0.08**	**2.78**	**-0.74**	**-0.45**
CO_2 (kg/km)	-13.92	1.72	65.54	-17.59	-10.89	**-0.56**	**0.07**	**2.62**	**-0.70**	**-0.44**

NOTE: The table reports the summary statistics for WTP values in € for the whole trip (10 days; 2000 km) for the sample of persons with rental experience. The WTP is computed based on the population distribution of the taste parameters for 10,000 randomly drawn individuals. Standard errors and confidence intervals are computed from 300 bootstrap resamples of the taste parameter draws. **Bold values**: computed from the estimates. Non-bold values: implied by the values from other designs. The implied WTP (FC) values based on the WTP (CO_2) are computed as WTP(CO_2)×25 for both engine types on average. The implied WTP (CO_2) values based on the WTP (FC) are computed as WTP(FC)/25 for both engine types on average.

Bibliography

Achtnicht, M. (2012). German Car Buyers' Willingness to Pay to Reduce CO2 Emissions. *Climatic Change*, 113(3-4):679–697.

Agarwal, M. K. and Ratchford, B. T. (1980). Estimating Demand Functions for Product Characteristics: The Case of Automobiles. *Journal of Consumer Research*, 7(3):249–262.

Allcott, H. (2011). Consumers' Perceptions and Misperceptions of Energy Costs. *American Economic Review*, 101(3):98–104.

Allcott, H. and Greenstone, M. (2012). Is There an Energy Efficiency Gap? *Journal of Economic Perspectives*, 26(4):3–28.

Allcott, H. and Knittel, C. (2017). Are Consumers Poorly Informed about Fuel Economy? Evidence from Two Experiments. Technical report, National Bureau of Economic Research, Cambridge, MA.

Allcott, H., Knittel, C., and Taubinsky, D. (2015). Tagging and Targeting of Energy Efficiency Subsidies. *American Economic Review: Papers & Proceedings*, 105(5):187–191.

Allcott, H., Mullainathan, S., and Taubinsky, D. (2014). Energy Policy with Externalities and Internalities. *Journal of Public Economics*, 112:72–88.

Allcott, H. and Taubinsky, D. (2015). Evaluating Behaviorally Motivated Policy: Experimental Evidence from the Lightbulb Market. *American Economic Review*, 105(8):2501–2538.

Allcott, H. and Wozny, N. (2014). Gasoline Prices, Fuel Economy, and The Energy Paradox. *The Review of Economics and Statistics*, 96(5):779–795.

Allenby, G. M. and Rossi, P. E. (1998). Marketing Models of Consumer Heterogeneity. *Journal of Econometrics*, 89(1-2):57–78.

Anderson, S. T., Kellogg, R., and Sallee, J. M. (2013). What Do Consumers Believe About Future Gasoline Prices? *Journal of Environmental Economics and Management*, 66(3):383–403.

Arguea, N. M., Hsiao, C., and Taylor, G. A. (1994). Estimating Consumer Preferences Using Market Data - An Application to Us Automobile Demand. *Journal of Applied Econometrics*, 9(1):1–18.

Aribarg, A., Burson, K. A., and Larrick, R. P. (2017). Tipping the Scale: The Role of Discriminability in Conjoint Analysis. *Journal of Marketing Research*, 54(2):279–292.

Atkinson, S. E. and Halvorsen, R. (1984). A New Hedonic Technique for Estimating Attribute Demand: An Application to the Demand for Automobile Fuel Efficiency. *The Review of Economics and Statistics*, 66(3):417–426.

Avineri, E. (2012). On the Use and Potential of Behavioural Economics from the Perspective of Transport and Climate Change. *Journal of Transport Geography*, 24:512–521.

Avineri, E. and Waygood, D. E. O. (2013). Applying Valence Framing to Enhance the Effect of Information on Transport-Related Carbon Dioxide Emissions. *Transportation Research Part A: Policy and Practice*, 48:31–38.

Bajari, P. and Benkard, C. L. (2005). Demand Estimation with Heterogeneous Consumers and Unobserved Product Characteristics: A Hedonic Approach. *Journal of Political Economy*, 113(6):1239–1276.

Bajari, P. and Kahn, M. E. (2005). Estimating Housing Demand With an Application to Explaining Racial Segregation in Cities. *Journal of Business & Economic Statistics*, 23(1):20–33.

Baltas, G. and Saridakis, C. (2013). An Empirical Investigation of the Impact of Behavioural and Psychographic Consumer Characteristics on Car Preferences: An Integrated Model of Car Type Choice. *Transportation Research Part A: Policy and Practice*, 54:92–110.

Bateman, I., Carson, R., Day, B., Hanemann, M., Hanley, N., Hett, T., Jones-Lee, M., and Loomes, G. (2002). *Economic Valuation with Stated Preference Techniques*. Edward Elgar Publishing.

Bento, A. M., Goulder, L. H., Jacobsen, M. R., and von Haefen, R. H. (2009). Distributional and Efficiency Impacts of Increased US Gasoline Taxes. *American Economic Review*, 99(3):667–699.

Bento, A. M., Li, S., and Roth, K. (2012). Is There an Energy Paradox in Fuel Economy? A Note on the Role of Consumer Heterogeneity and Sorting Bias. *Economics Letters*, 115(1):44–48.

Berkovec, J. and Rust, J. (1985). A Nested Logit Model of Automobile Holdings for One Vehicle Households. *Transportation Research Part B: Methodological*, 19(4):275–285.

Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile Prices in Market Equilibrium. *Econometrica*, 63(4):841–890.

Best, H. (2011). Methodische Herausforderungen: Umweltbewusstsein, Feldexperimente und die Analyse umweltbezogener Entscheidungen. In (Hrsg.), M. G., editor, *Handbuch Umweltsoziologie*, pages 240–258. VS Verlag für Sozialwissenschaften, Wiesbaden.

Bhat, C. R. (2001). Quasi-Random Maximum Simulated Likelihood Estimation of the Mixed Multinomial Logit Model. *Transportation Research Part B: Methodological*, 35(7):677–693.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2013). Salience and Consumer Choice. *Journal of Political Economy*, 121(5):803–843.

Boyd, J. and Mellman, R. E. (1980). The Effect of Fuel Economy Standards on the U.S. Automotive Market: An Hedonic Demand Analysis. *Transportation Research Part A: General*, 14(5-6):367–378.

Breidert, C., Hahsler, M., and Reutterer, T. (2006). A Review of Methods for Measuring Willingness-To-Pay. *Innovative Marketing*, 2(4):8–32.

Burson, K. a., Larrick, R. P., and Lynch, J. G. (2009). Six of One , Half Dozen of the Other. *Psychological Science*, 20(9):1074–8.

Busse, M. R., Knittel, C. R., Silva-Risso, J., and Zettelmeyer, F. (2016). Who is Exposed to Gas Prices? How Gasoline Prices Affect Automobile Manufacturers and Dealerships. *Quantitative Marketing and Economics*, 14(1):41–95.

Busse, M. R., Knittel, C. R., and Zettelmeyer, F. (2013). Are Consumers Myopic? Evidence from New and Used Car Purchases. *American Economic Review*, 103(1):220–256.

Busse, M. R., Pope, D. G., Pope, J. C., and Silva-Risso, J. (2015). The Psychological Effect of Weather on Car Purchases. *The Quarterly Journal of Economics*, 130(1):371–414.

Cadario, R., Parguel, B., and Benoit-Moreau, F. (2016). Is Bigger Always Better? The Unit Effect in Carbon Emissions Information. *International Journal of Research in Marketing*, 33(1):204–207.

Camilleri, A. R. and Larrick, R. P. (2014). Metric and Scale Design as Choice Architecture Tools. *Journal of Public Policy & Marketing*, 33(1):108–125.

Carlsson, F. and Martinsson, P. (2001). Do Hypothetical and Actual Marginal Willingness to Pay Differ in Choice Experiments? *Journal of Environmental Economics and Management*, 41:179–192.

Chang, H., Zhang, L., and Xie, G. X. (2015). Message Framing in Green Advertising: The Effect of Construal Level and Consumer Environmental Concern. *International Journal of Advertising*, 34(1):158–176.

Cohen, M. A. and Vandenbergh, M. P. (2012). The Potential Role of Carbon Labeling in a Green Economy. *Energy Economics*, 34:S53–S63.

Coller, M. and Williams, M. B. (1999). Eliciting Individual Discount Rates. *Experimental Economics*, 2(2):107–127.

Dahl, C. a. (2012). Measuring Global Gasoline and Diesel Price and Income Elasticities. *Energy Policy*, 41:2–13.

De Borger, B., Mulalic, I., and Rouwendal, J. (2016). Measuring the Rebound Effect with Micro Data: A First Difference Approach. *Journal of Environmental Economics and Management*, 79:1–17.

DellaVigna, S. (2009). Psychology and Economics: Evidence from the Field. *Journal of Economic Literature*, 47(2):315–372.

Delsaut, M. (2014). The Effect of Fuel Price on Demands for Road and Rail Travel: An Application to the French Case. *Transportation Research Procedia*, 1(1):177–187.

Dickey, D. A. and Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association*, 74(366):427–431.

Ding, M. (2007). An Incentive-Aligned Mechanism for Conjoint Analysis. *Journal of Marketing Research*, 44(2):214–223.

Dreyfus, M. K. and Viscusi, W. K. (1995). Rates of Time Preferences and Consumer Valuations of Automobile Safety and Fuel Efficiency. *Journal of Law and Economics*, 38(1):79–105.

Dubin, J. A. and Mcfadden, D. L. (1984). An Econometric Analysis of Residential Electric Appliance Holdings and Consumption. *Econometrica*, 52(2):345–362.

Efron, B. and Tibshirani, R. (1986). Bootstrap Methods for Standard Errors, Confidence Intervals, and Other Measures of Statistical Accuracy. *Statistical Science*, 1(1):54–75.

Elshiewy, O., Guhl, D., and Boztug, Y. (2017a). Multinomial Logit Models in Marketing - From Fundamentals to State-of-the-Art. *Marketing ZFP*, 39(3):32–49.

Elshiewy, O., Zenetti, G., and Boztug, Y. (2017b). Differences Between Classical and Bayesian Estimates for Mixed Logit Models: A Replication Study. *Journal of Applied Econometrics*, 32(2):470–476.

Enki, D. G., Trendafilov, N. T., and Jolliffe, I. T. (2013). A Clustering Approach to Interpretable Principal Components. *Journal of Applied Statistics*, 40(3):583–599.

Espey, M. and Nair, S. (2005). Automobile Fuel Economy: What is it Worth? *Contemporary Economic Policy*, 23(3):317–323.

Fan, Q. and Rubin, J. (2010). Two-Stage Hedonic Price Model for Light-Duty Vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, 2157(2157):119–128.

Feng, Y., Fullerton, D., and Gan, L. (2013). Vehicle Choices, Miles Driven, and Pollution Policies. *Journal of Regulatory Economics*, 44(1):4–29.

Fetscherin, M. and Toncar, M. (2009). Valuating Brand Equity and Product Related Attributes in the Context of the German Automobile Market. *Journal of Brand Management*, 17(2):134–145.

Flamm, B. (2009). The Impacts of Environmental Knowledge and Attitudes on Vehicle Ownership and Use. *Transportation Research Part D: Transport and Environment*, 14(4):272–279.

Foxman, E. R., Berger, P. W., and Cote, J. A. (1992). Consumer Brand Confusion: A Conceptual Framework. *Psychology and Marketing*, 9(2):123–141.

Frederiks, E. R., Stenner, K., and Hobman, E. V. (2015). The Socio-Demographic and Psychological Predictors of Residential Energy Consumption: A Comprehensive Review. *Energies*, 8(1):573–609.

Frondel, M. and Vance, C. (2009). Do High Oil Prices Matter? Evidence on the Mobility Behavior of German Households. *Environmental and Resource Economics*, 43(1):81–94.

Gensler, S., Hinz, O., Skiera, B., and Theysohn, S. (2012). Willingness-to-Pay Estimation with Choice-Based Conjoint Analysis: Addressing Extreme Response

Behavior with Individually Adapted Designs. *European Journal of Operational Research*, 219(2):368–378.

Gerarden, T., Newell, R. G., and Stavins, R. N. (2015). Deconstructing the Energy-Efficiency Gap: Conceptual Frameworks and Evidence. *American Economic Review*, 105(5):183–186.

Gillingham, K. (2014). Identifying the Elasticity of Driving: Evidence from a Gasoline Price Shock in California. *Regional Science and Urban Economics*, 47:13–24.

Gillingham, K. and Palmer, K. (2014). Bridging the Energy Efficiency Gap: Policy Insights from Economic Theory and Empirical Evidence. *Review of Environmental Economics and Policy*, 8(1):18–38.

Gleim, M. R., Smith, J. S., Andrews, D., and Cronin, J. J. (2013). Against the Green: A Multi-method Examination of the Barriers to Green Consumption. *Journal of Retailing*, 89(1):44–61.

Goldberg, P. K. (1995). Product Differentiation and Oligopoly in International Markets: The Case of the U.S. Automobile Industry. *Econometrica*, 63(4):891–951.

Goldberg, P. K. (1998). The Effects of the Corporate Average Fuel Efficiency Standards in the US. *The Journal of Industrial Economics*, XLVI(1).

Goodman, A. C. (1983). Willingness to Pay for Car Efficiency: A Hedonic Price Approach. *Journal of Transport Economics and Policy*, 17(3):247–266.

Gramlich, J. (2008). Gas Prices, Fuel Efficiency, and Endogenous Product Choice in the U.S. Automobile Industry. *Working Papers.*

Grankvist, G., Dahlstrand, U., and Biels, A. (2004). The Impact of Environmental Labelling on Consumer Preference: Negative vs. Positive Labels. *Journal of Consumer Policy*, 27(2):213–230.

Greene, D. L. (2010). How Consumers Value Fuel Economy: A Literature Review. *U.S. Environmental Protection Agency report EPA-420-R-10-008.*

Grigolon, L., Reynaert, M., and Verboven, F. (2017). Consumer Valuation of Fuel Costs and the Effectiveness of Tax Policy: Evidence from the European Car Market. *American Economic Journal: Economic Policy (Forthcoming).*

Gsottbauer, E. and van den Bergh, J. C. J. M. (2011). Environmental Policy Theory Given Bounded Rationality and Other-regarding Preferences. *Environmental and Resource Economics*, 49(2):263–304.

Guiot, D. and Roux, D. (2010). A Second-Hand Shoppers' Motivation Scale: Antecedents, Consequences, and Implications for Retailers. *Journal of Retailing*, 86(4):383–399.

Hackbarth, A. and Madlener, R. (2016). Willingness-to-Pay for Alternative Fuel Vehicle Characteristics: A Stated Choice Study for Germany. *Transportation Research Part A: Policy and Practice*, 85:89–111.

Hausman, J. a. (1979). Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables. *The Bell Journal of Economics*, 10(1):33–54.

Hayfield, T. and Racine, J. S. (2008). Nonparametric Econometrics: The np Package. *Journal of Statistical Software*, 27(5):1–32.

Heinzle, S. L. (2012). Disclosure of Energy Operating Cost Information: A Silver Bullet for Overcoming the Energy-Efficiency Gap? *Journal of Consumer Policy*, 35(1):43–64.

Helfand, G. and Wolverton, A. (2011). Evaluating the Consumer Response to Fuel Economy: A Review of the Literature. *International Review of Environmental and Resource Economics*, 5(2):103–146.

Hensher, D. A. (2006). Revealing Differences in Willingness to Pay due to the Dimensionality of Stated Choice Designs: An Initial Assessment. *Environmental and Resource Economics*, 34(1):7–44.

Hensher, D. a. (2010). Hypothetical Bias, Choice Experiments and Willingness to Pay. *Transportation Research Part B: Methodological*, 44(6):735–752.

Hess, S. and Train, K. (2017). Correlation and Scale in Mixed Logit Models. *Journal of Choice Modelling*, 23:1–8.

Hines, J. M., Hungerford, H. R., and Tomera, A. N. (1987). Analysis and Synthesis of Research on Responsible Environmental Behavior: A Meta-Analysis. *The Journal of Environmental Education*, 18(2):1–8.

Iacobucci, D., Posavac, S. S., Kardes, F. R., Schneider, M. J., and Popovich, D. L. (2015). The median split: Robust, refined, and revived. *Journal of Consumer Psychology*, 25(4):690–704.

Iyengar, S. S. and Lepper, M. R. (2000). When Choice is Demotivating: Can One Desire Too Much of a Good Thing? *Journal of Personality and Social Psychology*, 79(6):995–1006.

Jacobsen, M. R. and Van Benthem, A. A. (2015). Vehicle Scrappage and Gasoline Policy. *American Economic Review*, 105(3):1312–1338.

Jaffe, A. B. and Stavins, R. N. (1994). The Energy-Efficiency Gap. What Does It Mean? *Energy Policy*, 22(10):804–810.

Johnson, E. J., Shu, S. B., Dellaert, B. G., Fox, C., Goldstein, D. G., Häubl, G., Larrick, R. P., Payne, J. W., Peters, E., Schkade, D., Wansink, B., and Weber, E. U. (2012). Beyond Nudges: Tools of a Choice Architecture. *Marketing Letters*, 23(2):487–504.

Johnson, R. M. and Orme, B. K. (1996). How Many Questions Should You Ask in Choice-Based Conjoint Studies ? *Sawtooth Software Research Paper Series*, pages 1–24.

Kahn, J. A. (1986). Gasoline Prices and the Used Automobile Market: A Rational Expectations Asset Price Approach. *The Quarterly Journal of Economics*, 101(2):323–340.

Kaiser, F. G., Wolfing, S., and Fuhrer, U. (1999). Environmental Attitude and Ecological Behaviour. *Journal of Environmental Psychology*, 19:1–19.

Kalish, S. and Nelson, P. (1991). A Comparison of Ranking, Rating and Reservation Price Measurement in Conjoint Analysis. *Marketing Letters*, 2(4):327–335.

Kamakura, W. A., Kim, B.-D., and Lee, J. (1996). Modeling Preference and Structural Heterogeneity in Consumer Choice. *Marketing Science*, 15(2):152–172.

Keane, M. and Wasi, N. (2013). Comparing Alternative Models of Heterogeneity in Consumer Choice Behavior. *Journal of Applied Econometrics*, 28:1018–1045.

Klier, B. T. and Linn, J. (2010). The Price of Gasoline and New Vehicle Fuel Economy: Evidence from Monthly Sales Data. *American Economic Journal: Economic Policy 2*, 2(August):134–153.

Knittel, C. R. (2012). Automobiles on Steroids: Product Attribute Trade-Offs and Technological Progress in the Automobile Sector. *American Economic Review*, 101(December 2011):3368–3399.

Koenker, R. and Hallock, K. F. (2001). Quantile Regression. *Journal of Economic Perspectives*, 15(4):143–156.

Kohli, R. and Mahajan, V. (1991). A Reservation-Price Model for Optimal Pricing of Multiattribute Products in Conjoint Analysis. *Journal of Marketing Research*, 28(3):347.

Kollmuss, A. and Agyeman, J. (2002). Mind the Gap: Why do people act environmentally and what are the barriers to pro-environmental behavior? *Environmental Education Research*, 8(3):239–260.

Lacetera, N., Pope, D. G., and Sydnor, J. R. (2012). Heuristic Thinking and Limited Attention in the Car Market. *American Economic Review*, 102(5):2206–2236.

Lancaster, K. J. (1966). A New Approach to Consumer Theory. *Journal of Political Economy*, 74(2):132–157.

Langer, A. and Miller, N. H. (2013). Automakers' Short-Run Responses to Changing Gasoline Prices. *The Review of Economics and Statistics*, 95(4):1198–1211.

Larrick, R. P. and Soll, J. B. (2008). The MPG Illusion. *Science*, 320(5883):1593–1594.

Lembregts, C. and Pandelaere, M. (2013). Are All Units Created Equal? The Effect of Default Units on Product Evaluations. *Journal of Consumer Research*, 39(6):1275–1289.

Levin, I. P., Schneider, S. L., and Gaeth, G. J. (1998). All Frames Are Not Created Equal: A Typology and Critical Analysis of Framing Effects. *Organizational Behavior and Human Decision Processes*, 76(2):149–188.

Li, Q. and Racine, J. (2004). Cross-Validated Local Linear Nonparametric Regression. *Statista Sinica*, 14:485–512.

Li, S., Timmins, C., and von Haefen, R. H. (2009). How Do Gasoline Prices Affect Fleet Fuel Economy? *American Economic Journal: Economic Policy*, 1(2):113–137.

Manning, K. C. and Sprott, D. E. (2009). Price Endings, Left-Digit Effects, and Choice. *Journal of Consumer Research*, 36(2):328–335.

Matas, A. and Raymond, J.-L. (2009). Hedonic Prices for Cars: An Application to the Spanish Car Market, 19812005. *Applied Economics*, 41(22):2887–2904.

McFadden, D. (1973). Conditional Logit Analysis of Qualitative Choice Behavior. In Zarembka, P., editor, *Frontiers in Econometrics*, pages 105–142. Academic Press, New York.

McFadden, D. and Train, K. (2000). Mixed MNL Models for Discrete Response. *Journal of Applied Econometrics*, 15(5):447–470.

Metcalf, G. E. and Hassett, K. a. (1999). Measuring the Energy Savings from Home Improvement Investments: Evidence from Monthly Billing Data. *The Review of Economics and Statistics*, 81(3):516–528.

Meyer, A. (2015). Does education increase pro-environmental behavior? Evidence from Europe. *Ecological Economics*, 116:108–121.

Miles, M. P. and Covin, J. G. (2000). Environmental Marketing: A Source of Reputational Competitive and Financial Advantage. *Journal of Business Ethics*, 23:299–311.

Milfont, T. L. and Duckitt, J. (2010). The Environmental Attitudes Inventory: A Valid and Reliable Measure to Assess the Structure of Environmental Attitudes. *Journal of Environmental Psychology*, 30(1):80–94.

Miller, K. M., Hofstetter, R., Krohmer, H., and Zhang, Z. J. (2011). How Should Consumers' Willingness to Pay Be Measured? An Empirical Comparison of State-of-the-Art Approaches. *Journal of Marketing Research*, 48(1):172–184.

Mulalic, I. and Rouwendal, J. (2015). The Impact of Fixed and Variable Costs on Automobile Demand: Evidence from Denmark. *Economics of Transportation*, 4(4):227–240.

Münscher, R., Vetter, M., and Scheuerle, T. (2016). A Review and Taxonomy of Choice Architecture Techniques. *Journal of Behavioral Decision Making*, 29(5):511–524.

Murphy, J. J., Allen, P. G., Stevens, T. H., and Weatherhead, D. (2005). A Meta-Analysis of Hypothetical Bias in Stated Preference Valuation. *Environmental and Resource Economics*, 30(3):313–325.

Murray, J. and Sarantis, N. (1999). Price-Quality Relations and Hedonic Price Indexes for Cars in the United Kingdom. *International Journal of the Economics of Business*, 6(1):5–27.

Newell, R. and Siikamäki, J. V. (2015). Individual Time Preferences and Energy Efficiency. *American Economic Review: Papers & Proceedings*, 105(5):196–200.

Newell, R. G. and Siikamäki, J. (2014). Nudging Energy Efficiency Behavior: The Role of Information Labels. *Journal of the Association of Environmental and Resource Economists*, 1(4):555–598.

Ohta, M. and Griliches, Z. (1986). Automobile Prices and Quality: Did the Gasoline Price Increases Change Consumer Tastes in the U.S.? *Journal of Business & Economic Statistics*, 4(2):187–198.

Olson, E. L. (2013). It's Not Easy Being Green: The Effects of Attribute Tradeoffs on Green Product Preference and Choice. *Journal of the Academy of Marketing Science*, 41(2):171–184.

Pandelaere, M., Briers, B., and Lembregts, C. (2011). How to Make a 29% Increase Look Bigger: The Unit Effect in Option Comparisons. *Journal of Consumer Research*, 38(2):308–322.

Patterson, M. G. (1996). What is Energy Efficiency? Concepts, Indicators and Methodological Issues. *Energy Policy*, 24(5):377–390.

Pelham, B., Sumarta, T., and Myaskovsky, L. (1994). The Easy Path From Many To Much: the Numerosity Heuristic. *Cognitive Psychology*, 26(2):103–133.

Peters, A., Gutscher, H., and Scholz, R. W. (2011). Psychological Determinants of Fuel Consumption of Purchased New Cars. *Transportation Research Part F: Traffic Psychology and Behaviour*, 14(3):229–239.

Peters, E., Västfjäll, D., Slovic, P., Mertz, C., Mazzocco, K., and Dickert, S. (2006). Numeracy and Decision Making. *Psychological Science*, 17(5):407–413.

Poortinga, W., Steg, L., and Vlek, C. (2004). Values, Environmental Concern, and Environmental behavior: A Study into Household Energy Use. *Environment and Behavior*, 36(1):70–93.

Portnoy, S., Koenker, R., Thisted, R. A., Osborne, M. R., Portnoy, S., and Koenker, R. (1997). The Gaussian Hare and the Laplacian Tortoise: Computability of Squared-Error versus Absolute-Error Estimators. *Statistical Science*, 12(4):279–300.

Racine, J. (1993). An Efficient Cross-Validation Algorithm for Window Width Selection for Nonparametric Kernel Regression. *Communications in Statistics - Simulation and Computation*, 22:1107–1114.

Raghubir, P. and Srivastava, J. (2009). The Denomination Effect. *Journal of Consumer Research*, 36(4):701–713.

Requena-Silvente, F. and Walker, J. (2006). Calculating Hedonic Price Indices with Unobserved Product Attributes: An Application to the UK Car Market. *Economica*, 73(291):509–532.

Rey, T., Kordon, A., and Wells, C. (2012). *Applied Data Mining for Forecasting Using SAS*. Cary, NC: SAS Institute Inc.

Rosen, S. (1974). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy*, 82(1):34–55.

Sallee, J. M. (2014). Rational Inattention and Energy Efficiency. *The Journal of Law and Economics*, 57(3):781–820.

Sallee, J. M., West, S. E., and Fan, W. (2016). Do Consumers Recognize the Value of Fuel Economy? Evidence from Used Car Prices and Gasoline Price Fluctuations. *Journal of Public Economics*, 135:61–73.

Sanbonmatsu, D. M., Kardes, F. R., Houghton, D. C., Ho, E. a., and Posavac, S. S. (2003). Overestimating the Importance of the Given Information in Multiattribute Consumer Judgment. *Journal of Consumer Psychology*, 13(3):289–300.

Schouten, T. M., Bolderdijk, J. W., and Steg, L. (2014). Framing Car Fuel Efficiency: Linearity Heuristic for Fuel Consumption and Fuel-Efficiency Ratings. *Energy Efficiency*, 7(5):891–901.

Simon, H. A. (1955). A Behavioral Model of Rational Choice. *The Quarterly Journal of Economics*, 69(1):99.

Sonnier, G., Ainslie, A., and Otter, T. (2007). Heterogeneity Distributions of Willingness-to-pay in Choice Models. *Quantitative Marketing and Economics*, 5(3):313–331.

Sprei, F., Karlsson, S., and Holmberg, J. (2008). Better Performance or Lower Fuel Consumption: Technological Development in the Swedish New Car Fleet 19752002. *Transportation Research Part D: Transport and Environment*, 13(2):75–85.

Steg, L. (2005). Car Use: Lust and Must. Instrumental, Symbolic and Affective Motives for Car Use. *Transportation Research Part A: Policy and Practice*, 39(2-3):147–162.

Teisl, M. F., Rubin, J., and Noblet, C. L. (2008). Non-Dirty Dancing? Interactions Between Eco-Labels and Consumers. *Journal of Economic Psychology*, 29(2):140–159.

Thaler, R. H. and Shefrin, H. M. (1981). An Economic Theory of Self-Control. *Journal of Political Economy*, 89(2):392–406.

Thaler, R. H. and Sunstein, C. R. (2008). *Nudge: Improving Decisions about Health, Wealth, and Happiness.* Yale University Press.

Thaler, R. H., Sunstein, C. R., and Balz, J. P. (2014). Choice Architecture. *SSRN Electronic Journal*, pages 428–439.

Thomas, M. and Morwitz, V. (2005). Penny Wise and Pound Foolish: The Left-Digit Effect in Price Cognition. *Journal of Consumer Research*, 32(1):54–64.

Tietenberg, T. (2009). Reflections–Energy Efficiency Policy: Pipe Dream or Pipeline to the Future? *Review of Environmental Economics and Policy*, 3(2):304–320.

Train, K. and Weeks, M. (2005). Discrete Choice Models in Preference Space and Willingness-to Pay Space. In Alberini, A. and Scarpa, R., editors, *Applications* *of simulation methods in environmental and resource economics*. Dordrecht: Springer.

Train, K. E. (2009). *Discrete Choice Methods with Simulation*. Cambridge University Press, Cambridge.

Train, K. E. and Winston, C. (2007). Vehicle choice behavior and the declining market share of U.S. automakers. *International Economic Review*, 48(4):1469–1496.

Triplett, J. E. (1969). Automobiles and Hedonic Quality Measurement. *Journal of Political Economy*, 77(3):408–417.

Tsvetanov, T. and Segerson, K. (2013). Re-evaluating the Role of Energy Efficiency Standards: A Behavioral Economics Approach. *Journal of Environmental Economics and Management*, 66(2):347–363.

Turrentine, T. S. and Kurani, K. S. (2007). Car Buyers and Fuel Economy? *Energy Policy*, 35(2):1213–1223.

Tversky, A. and Kahneman, D. (1981). The Framing of Decisions and the Psychology of Choice. *Science*, 211(4481):453–458.

UBA (2016). Mit Welchen Kenngrößen Kann Umweltbewusstsein Heute Erfasst Werden? Eine Machbarkeitsstudie. *UBA Publikationen*, 58/2016:134.

Ungemach, C., Camilleri, A. R., Johnson, E. J., Larrick, R. P., and Weber, E. U. (2017). Translated Attributes as Choice Architecture: Aligning Objectives and Choices Through Decision Signposts. *Management Science*, 64(5):2445–2459.

Uri, N. D. (1988). The Market Valuation of New Car Quality. *Transportation Research Part A: General*, 22A(5):361–373.

van den Bergh, J. C. (2008). Environmental Regulation of Households: An Empirical Review of Economic and Psychological Factors. *Ecological Economics*, 66(4):559–574.

Van den Brink, R. M. and Van Wee, B. (2001). Why has Car-Fleet Specific Fuel Consumption Not Shown Any Decrease Since 1990? Quantitative Analysis of Dutch Passenger Car-Fleet Specific Fuel Consumption. *Transportation Research Part D: Transport and Environment*, 6(2):75–93.

Verlegh, P. W., Schifferstein, H. N., and Wittink, D. R. (2002). Range and Number-of-Levels Effects in Derived and Stated Measures of Attribute Importance. *Marketing Letters*, 13(1):41–52.

Voelckner, F. (2006). An Empirical Comparison of Methods for Measuring Consumers' Willingness to Pay. *Marketing Letters*, 17(2):137–149.

Wadhwa, M. and Zhang, K. (2015). This Number Just Feels Right: The Impact of Roundedness of Price Numbers on Product Evaluations. *Journal of Consumer Research*, 41(5):1172–1185.

Walsh, G., Hennig-Thurau, T., and Mitchell, V.-W. (2007). Consumer Confusion Proneness: Scale Development, Validation, and Application. *Journal of Marketing Management*, 23(7-8):697–721.

West, S. E. (2004). Distributional Effects of Alternative Vehicle Pollution Control Policies. *Journal of Public Economics*, 88(3-4):735–757.

Wittink, D. R., Krishnamurthi, L., and Reibstein, D. J. (1990). The Effect of Differences in the Number of Attribute Levels on Conjoint Results. *Marketing Letters*, 1(2):113–123.

Xie, G.-X. and Kronrod, A. (2012). Is the Devil in the Details? *Journal of Advertising*, 41(4):103–117.

Appendix A

Supplementary Material

This section describes the supplementary material for the empirical investigations presented in the thesis that includes datasets, variable descriptions, code files, and a questionnaire. All records are available in digital form on the CD accompanying the thesis.

A1. The Moderating Effect of Fuel Prices on the Market Value of Fuel Economy, Driving Intensity, and CO_2 Emissions

Dataset: The dataset "cardata.sas7bdat" contains information for car models produced over the period from 2011 to 2013 that is retrieved from a web database ADAC (http://www.adac.de/infotestrat/autodatenbank/default.aspx). The values for new passenger car registrations per year are additionally retrieved from the German Federal Motor Transport Authority (Kraftfahrtbundesamt; http://www.kba.de).

Variable description: VarDescription1.pdf

Code file: cardata_analysis.sas

A2. On Factors of Consumer Heterogeneity in (Mis)valuation of Future Energy Costs: Evidence for the German Automobile Market

Dataset: The dataset "carsurvey.csv" used in the study is provided by a market research company for (non-commercial) scientific research. A sample of new car buyers in Germany was surveyed briefly after the purchase (within the first 3 months). The survey was conducted by phone (CATI). No information on the response rate is available. The dataset contains information on the car models purchased by a sample of consumers along with the car attributes, prices paid for the chosen cars, and various consumer- and purchase-related characteristics. For the analysis, a sample of private buyers of cars with gasoline or diesel engines from six car classes over a time period of 7 years is used. Due to privacy issues, all information that could help track a concrete car make or a buyer has been de-identified. According to the data use agreement, the dataset cannot be transferred to anyone besides the editors and reviewers for the purposes of evaluating the manuscript. Unauthorized uses, disclosures, or sharing of the dataset is prohibited.

Variable description: VarDescription2.pdf

Code files: The code is written mainly in SAS (file: carsurvey.sas). For the nonparametric hedonic price regression, the "NP" package of R (Hayfield and Racine, 2008) is used (file: NPHP.R)

A3. Metric and Scale Effects in Willingness-to-Pay for Environmental Benefits

Datasets: The dataset "ExperimentData.sas7bdat" contains responses of the participants in the online survey based on the questionnaire provided in the file "Questionnaire.pdf". The author developed the questionnaire and supervised the collection of data by herself. A convenience sample for the data collection was used. Participants were recruited online from July to November 2017 via social media networks, networks of students from German universities, and various online platforms to collect data (e.g., PollPool, SurveyCircle). Respondents were incentivized by the chance to win one of 10×20-euro Amazon gift cards. The questionnaire was offered in either English or German. Only individuals who were 18 years of age or older were eligible to complete the survey. The file "DataEst.csv" contains the data in a choice format for estimating discrete choice models. The file "RDataSimShare.csv" provides data for the market simulation. The file "HHDesign.csv" contains the designs of the choice-based conjoint experiments for testing the efficiency of the designs on simulated choices, which are generated following random utility theory.

Variable description: VarDescription3.pdf

Code files: The file "ExperimentData_analysis.sas" contains the code for converting the dataset "ExperimentData.sas7bdat" into a choice form for a subsequent estimation of discrete choice models. The file "DataEst_analysis.R" contains the code for testing of the choice-based conjoint experimental designs and analyzing the collected choice data with discrete choice models.

Selbstständigkeitserklärung

Ich versichere, die von mir vorgelegte Dissertation selbständig und ohne unerlaubte Hilfe und Hilfsmittel angefertigt, sowie die benutzten Quellen und Daten anderen Ursprungs als solche kenntlich gemacht zu haben.

Ich bezeuge durch meine Unterschrift, dass meine Angaben über die bei der Abfassung meiner Dissertation benutzten Hilfsmittel, über die mir zuteil gewordene Hilfe sowie über frühere Begutachtungen meiner Dissertation in jeder Hinsicht der Wahrheit entsprechen.

Berlin, 30. Juli 2018

Vlada Pleshcheva